TRAJECTORY MODELLING OF AN ARTILLERY SHELL USING CONVENTIONAL AND NEURAL MODELLING

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CERTIFICATE

It is certified that the work contained in this thesis entitled, **"Trajectory Modelling of an Artillery Shell using Conventional and Neural Models"** by Ayush Jha has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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ABSTRACT

The advent of high-altitude performance artillery shells have made the consideration of various factors causing trajectory deviations or dispersions a necessity. During past decade, several procedures were formulated for calculating the effect of wind and results of the flight made with the use of these methods have been good in some cases and very poor in others.

In recent times, the most widely used trajectory modeling for artillery shells has been via mathematical models such as point-mass model, modified point-mass model and six-degrees-of-freedom model. Application of these require an a priori postulation of equations of motion governing the shell trajectory and to solve these equations, one need reliable estimates of aerodynamic coefficients. Due to various assumption used in arriving at the mathematical models and also due to non-availability of reliable estimates of aerodynamic coefficients required to solve these equations, an alternate approach of using general function approximation capability of feed forward neural networks (FFNNs) for estimating shell performance under varying wind conditions is explored. Further, a attempt has been made to predict the whole trajectory of the shell, rather than only range or drift of shell when fired under varying/constant wind conditions.

The present work addresses this aspect by way of proposing four neural models for predicting trajectory variables. The estimated trajectory parameter compare well with the measured data.

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Ayush Jha

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NOMENCLATURE

C_N, C_A	= Coefficient of normal and axial force
C_L, C_{Do}, C_M	= Non-dimensional lift, drag, and pitching moment coefficients
C_X, C_Y, C_Z	= Coefficient longitudinal, lateral, vertical force
Cd_c	= Drag coefficient which should be experienced by a circular cylinder section of radius r at Reynolds number and Mach number based upon the diatmeter and the cross component velocity (vsinα)
d	= Diameter of Rocket, mm
g	= Acceleration due to gravity, m/s^2
I_x, I_y	= Moment of inertia about x and y axis, kgm^2
I_{xy}, I_{xz}, I_{yz}	= Cross products of inertia, kgm^2
m	= mass, kg
P	=Ballistic Air Pressure (ambient Air Pressure), mm Hg
p	= Roll rate, rad/sec or deg/sec
q	= Pitch rate, red/sec or deg/sec
r	= yaw rate, red/sec or deg/sec
$\bar{q}$	= Dynamic pressure, N/m^2
R	= Range, m
s	= Reference area m^2
T	=Ballistic Air Temperature (ambient air temperature), C
u,v,w	= Velocity components in x, y and z body axes, m/s
v	= Air-relative speed, m/s
W_x, W_y, W_z	= Head/tailwind, crosswind, vertical wind components (m/s)

α = angle of attack, rad or deg

β = angle of side slip, rad or deg

θ = Firing Table Elevation, Firing angle, mils

η = Ratio of drag coefficient of a circular cylinder of finite length to that of a circular cylinder of infinite length

θ = Pitch attitude, mils

ϕ = Roll attitude, rad or deg

ψ = Heading angle, rad or sec

Superscript

• = Derivative with respect to time

Subscript

o = Initial conditions

x,y,z = component along x, y, and z direction

wind = wind axes

Stability and control derivatives

$C_{L\alpha} = \partial C_L/\partial\alpha$, $C_{Lq} = \partial C_L/\partial(qd/2V)$, $C_{L\delta} = \partial C_L/\partial\delta$

$C_{m\alpha} = \partial C_m/\partial\alpha$, $C_{mq} = \partial C_m/\partial(qd/2V)$

$C_{lp} = \partial C_l/\partial(pd/2V)$, $C_{l\delta} = \partial C_l/\partial\delta$

$C_{n\beta} = \partial C_n/\partial\beta$, $C_{nr} = \partial C_n/\partial(rd/2V)$

$C_{y\beta} = \partial C_y/\partial\beta$, $C_{yr} = \partial C_y/\partial(rd/2V)$

CHAPTER 1

INTRODUCTION

Artillery gun systems are used to support personnel in contact with the enemy in forward areas The artillery has lived up to its reputation of softening the fiercely defending enemy targets and thus making way for successful infantry assaults in the forward areas The role of the field artillery is to provide fire support to other arms by backing up attacks, providing defensive fire, neutralizing an enemy's gun emplacements and generally acting as a basis around which all other arms can operate The modern field guns or howitzers are high angle long barrel weapons, which provide long distance plunging fire Modern technology has transformed the artillery gun so radically that it now bears little resemblance to its predecessors. Up to the beginning of the Second World War, 75mm was widely used, but by the time the war ended caliber (diameter) had increased to around 105mm. The caliber was stepped up to 155mm in the 1960's when it became apparent that 105mm projectile could not disrupt armored formation During recent decades performance of artillery has shown dramatic improvements

Artillery gun systems are used to fire artillery shells A shell may be high explosive (HE) when it is filled with a substance, e.g., Tri nitro toluene (TNT) which detonates on being suitably initiated, or may be a "carrier shell" i.e., designed to carry smoke canisters, illuminates, chemicals, etc which are ejected by a small charge initiated by time fuze

Generally gun launched artillery shells are spin stabilized and are composed of low drag nose incorporating cylindrical body with a driving band at the rear to impart spin-in-bore and a low drag after body.

System accuracy is probably the most important consideration in artillery system Accuracy is the measure of the ability of the shell to position the payload at a given point The accuracy of the artillery shell depends on the following major factors:[1]

1. Muzzle velocity irregularity due to variation in charge
2. Jump and throw-off. This occurs due to recoiling effect of gun Due to this action, there is vertical component known as jump and there is a horizontal component of that force known as throw-off.
3. Differences between shells due to shape, size, etc
4. Meteorological effects, like ambient temperature, density, head/tail wind, crosswind etc

Dispersion caused by the first four major factors can be greatly reduced by imposing proper manufacturing and assembly tolerances. Wind dispersion can be made less significant by use of wind-compensation procedure which gives the launch azimuth and elevation angle necessary to achieve the desired trajectory[2]

The advent of high-altitude-performance artillery shells have made the consideration of factors causing trajectory deviations or dispersion a necessity. One of the main contributors to the dispersion of an unguided vehicle is wind. During the past decade several theories have been proposed for calculating wind compensation and results of flight made with the use of these methods have been good in some cases and very poor in others[2]

Accurate trajectory simulation is of paramount importance for evolving wind compensation procedure. The requirements for a trajectory program needed for a wind compensation procedure are 1) that the trajectory be three dimensional, 2) that provision be made for arbitrary wind velocity and 3) that non-linear aerodynamics with respect to flow incidence angle be included. The first two requirements are obvious since, in the consideration of side winds, the trajectory is three dimensional and the wind velocity is arbitrary. The third requirement is imposed because most of the spinning artillery shells when fired at high angle elevations (θ>45 degrees) experience large angle of attack (around 40°) near the vertex of the trajectory.

Conventional approach hitherto for understanding the inflight behavior of projectiles was to develop mathematical models that could predict all elements of the

trajectory from launch to target To this purpose, it becomes essential that all forces, moments affecting the flight of the projectile are accounted for in a well defined mathematical form[1] Beginning with the most simple but relatively inaccurate mathematical model, the in-vacuo trajectory model, more and more sophisticated models of increasing accuracy such as the point mass model, the modified point mass model and the six –degrees-of freedom model have been developed[1]. A brief description of these models is given in Chapter 3 Presently we only wish to point out that even the best of these proposed models have their limitations due to their inability to model all the problem variables adequately. For example, the initial conditions at the time of shell leaving the barrel are not accounted for by any of the proposed mathematical models Furthermore, the trajectory require a large number of aerodynamic coefficients (linear or nonlinear) as input and the estimates available for these coefficients are not so reliable[1].

It is thus realized that even the best of the mathematical models available to date are not reliable because accurate prediction is difficult for the range obtainable for various elevations. The limitations of the mathematical models so far used for predicting the performances of artillery shell necessitated researchers to look at an alternative approach to modeling The feed forward neural network[3,4,5] provides one such potential way of modeling The neural network have been successfully used in such diverse fields as signal processing, pattern recognition, system identification and control. In recent years, neural models of aircraft aerodynamics have been successfully developed for many applications relevant to Aerospace Engineering[6,7,8] For example neural modeling has been used for estimating aircraft stability and control derivatives of stable[9,10,11], unstable[12] and aeroelastic aircraft[13]. It was envisaged that a neural model can be developed to replace the use of hitherto used mathematical models for solving the shell trajectory related problems Recently, the validity of the neural modeling was demonstrated for different application relevant to artillery shells[14] .In this work, study was carried out to predict artillery performances for known firing angle (θ) or to predict firing angle required for desired range using various neural models However, the results were valid for constant value of the head/tail wind and crosswind. It was assumed that constant wind had existed at different altitudes through which the shell passed. This is an approximation

to varying wind condition at different altitudes through which the shell passes It was suggested to search for a way to account for varying wind conditions in neural modeling[14] for performance prediction The neural models then could be used to predict range and drift for artillery shells, these when fired at different elevations under varying wind conditions. However, none of these neural models are capable of predicting the spatial coordinates of the flight path (trajectory) traced by the center of gravity of the shell. It was also recommended to carry out study for trajectory predictions incorporating effect of varying wind using models like point-mass model, modified point-mass model and six-degrees-of-freedom model. A comparison of values from these models and neural models would show relative reliability of the predicted values for real life applications[14].

Investigation has to be carried out to identify the relevant set of input-output variables for the network for modeling the effect of varying wind Further, a suitable architecture for the neural network is to be searched to achieve acceptable functional mapping between the input-output variables for each of the problem As far as conventional method is concerned, search has to be made to incorporate the effect of high angle of attack through appropriate aerodynamic modeling. Finally a comparison of predicted output from conventional and neural model has to be carried out to asses the relative reliability of the predicted value for real life applications

In the present work, all the above problems are addressed and adequately solved For demonstrating the prediction capability of neural models developed, the data used for this study is for 155 mm artillery shell supplied by Armament Research and Development Establishment, Pune. Details of various conventional models and neural models for performance predictions are given in Chapter 3. The details of conventional and neural models along with results and discussions are given in Chapter 4 A brief review of the neural network proceeds these Chapter 3 and 4, and is given in Chapter 2 The dissertation ends with Chapter 5 containing conclusions and few suggestions for future work.

CHAPTER 2

ARTIFICIAL NEURAL NETWORKS

2.1 Introduction

A neural network is a parallel-distributed processor that has a natural propensity for storing experimental knowledge and making it available for use It resembles the brain in two respects, 1) Knowledge is acquired by the network through learning process, 2) Inter neuron connection strengths known as synaptic weights are used to store the knowledge. Neural networks are also referred to in the literature[3,4,5] as neuro computers, connectionist networks, parallel distributed processors, etc

Artificial neural networks consist of group of neurons arranged in a layered structure Each neuron receives signal from the neurons in the layer previous to itself and passes a signal on to the neuron in the following layer The relationship between the summed inputs to a neuron and its output is governed by an 'activation function'[4] Some of the commonly employed activation functions are the step functions, the tangent-hyperbolic function, and the logistic (sigmoidal) function.

Out of these, the most often used activation function is the sigmoidal function defined as

$$F(x) = \frac{1}{1+e^{-x/\lambda}}$$

where λ is logistic gain,

The sigmoidal function is continuous, monotonically increasing and continuously differentiable, and it asymptotically approaches fixed finite values as the input approaches infinity (+ or -)

Amongst the artificial neural networks, the feed forward neural networks (FFNNs) have found the favour with most researchers for applications in aerospace engineering problems [6,7,8] The feed forward neural networks consists of source nodes that constitute the input layer and one or more hidden layers and an output layer. Feed forward neural networks have neurons arranged in layers like directed graphs, implying a unidirectional flow of signals, and thus are static in nature This kind of modeling develops input-output relationship of a black-box kind Each of the connection between neurons is assigned its individual weight and it is adjusted so as to yield the required output corresponding to the known set of inputs Assignments of weights is done during the training sessions of the network

2.2 Back Propagation Algorithm

One of the efficient methods for training the FFNN is the back propagation algorithm (BPA) Back propagation algorithm consists of a forward and backward pass through different layers of the network During the forward pass, input vector is applied to the input nodes of the network and its effect propagates through the network layer by layer. The connective weights are all kept fixed during the forward pass On the other hand, in the backward pass, the weights are updated in accordance with error correction rule. Specifically, the actual response of the networks is subtracted from the desired response to produce an error signal The signal is then propagated backward against the direction of the connective weights. There are four steps for back propagation algorithm

a) Initialization. Start with a reasonable network configuration and set all the synaptic weights randomly

b) Forward Computation Let a training example represented by x(n) be applied to the input nodes Then the output of the network is computed by proceeding through the network, layer by layer Next, the error signal is computed using difference between the desired response vector and the output vector

c) Backward computation: The back propagation algorithm is based on optimizing a suitably defined error function At each point, the local output error cost function defined by the sum of the squared error is computed. The weights of the network are adjusted in such a way that the mean squared error (MSE) is minimized.

The MSE is given by

$$\mathrm{MSE} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [Yi(j) - Xi(j)]^2$$

where Y and X are the desired and predicted outputs, n is the number of data points and m is the number of output variables

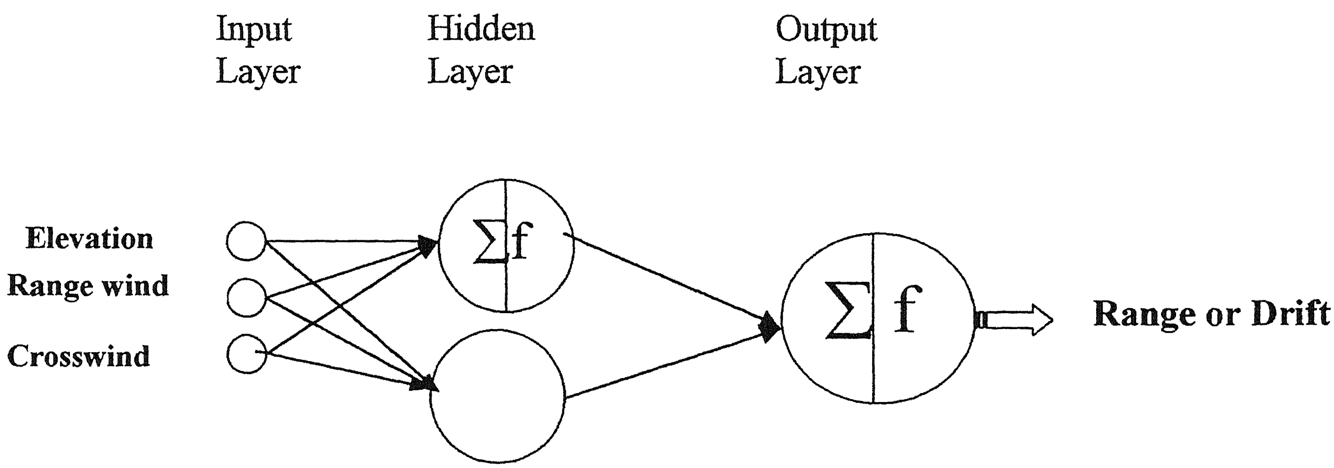
d). Step (b) to (c) are repeated for each training pair in the training set until the error for the entire set is less than the prescribed value or the number of iterations exceed the prescribed limit

The training algorithm is recursive in nature and it needs repetitive training sessions to achieve the required learning There are many network influential (tuning) parameters like the learning rate, the momentum rate, the number of hidden layers, the number of iterations, the logistic gain, etc, that affect the accuracy of functional mapping between the input and the output variables. There are no set rules for fixing values of these influential parameters. In literature, a few guidelines are available to guide the choice of these parameters. However, the final choices of fine tuning these parameters is to be achieved by trial and error for the given problem, and it is a crucial step in finding a

suitable neural model for the problem Some of the guidelines and thumb rules for training of neural networks are given in Appendix A

The neural network model is first trained on the known sets of input-output pairs of experimental or recorded data The trained network is then capable of predicting the required output based on known (measured) input variables. This approach does not require a mathematical model or a transfer function relating the input-output data but only a sufficient set of input-output pairs of data The choice of inputs that are likely to affect the output to be predicted by the neural model is of critical importance The selection of inputs for the given problem is based on the understanding of the physics of the problem and engineering judgment.

In the present work, a neural model is proposed for the trajectory modeling of an artillery shell fired from a gun A non-linear relationship is mapped by the neural network between the input variables such as angle of firing (θ), head wind (W_x), cross wind (W_y), with the output variables, such as range, drift etc. A schematic of such neural model is shown in Fig 2.1. For a typical model used in the present work, the choice of the input and output variables for mapping projectile dynamics is dictated by the physical understanding of the phenomenon governing the shell dynamics. Once the input and output variables for the feed forward artificial network (FFNN) are selected, the FFNN model of the shell dynamics is achieved without the need of a formal model structure formulation.



$$f = \frac{1}{1 + e^{-x/\lambda}}$$

Fig. 2.1 Schematic of feed forward neural networks.

CHAPTER 3

TRAJECTORY AND RANGE MODELLING OF ARTILLERY SHELL

3.1 General

Artillery shells are class of projectiles, which still continue to be of interest and further investigations for many aero-ballisticians and user agencies. In the present work, we are specifically to focus on flight of a spin stabilized, dynamically stable, unguided artillery shell.

Presently, the conventional approach to account for the effect of wind in trajectory modeling has been by postulating a suitable mathematical model consisting of equations of motion. There are numerous such forms of trajectory model involving different basic assumptions and having different complexities of solution[1]. We shall briefly outline few of them in subsequent sections.

3.2 Point-Mass Model (PM)

In this model, it is assumed that only aerodynamic force acting on the projectile is drag. It provides fairly accurate estimates of range for an adequately stable projectile and can be used to estimate the first order effects of wind. However, this model does not account for the effect of spin, lift, side force, pitching and yawing moment of the projectile and thus fails to predict, drift experienced by spinning shell. To estimate first order wind effects, point-mass equations of motion of projectiles may be expressed as follows[1].

$$\frac{d^2x}{dt^2} = -\frac{\pi\rho d^2 C_D}{8m} v\left(\frac{dx}{dt} - W_x\right) \tag{3.1a}$$

$$\frac{d^2y}{dt^2} = -g - \frac{\pi\rho d^2 C_D}{8m} v\left(\frac{dy}{dt} - W_y\right) \tag{3.1b}$$

$$\frac{d^2z}{dt^2} = -\frac{\pi\rho d^2 C_D}{8m} v\left(\frac{dz}{dt} - W_z\right) \tag{3.1c}$$

where x denotes the range, y the height and z the drift, and W_x, W_y, W_z are the respective components of the wind velocity **W** along x, y and z directions.

3.3 Modified Point Mass Model (MPM)

The modified point mass model is also known as four degrees-of-freedom model (three spatial degrees-of-freedom plus axial spin). Its basis is conventional point-mass model in addition the instantaneous equilibrium yaw is calculated at each time step along the trajectory so as to provide estimates of yaw, drag, drift and magnus force effects resulting from the yaw of repose[1]. The modified point-mass equation of motion are given as

$$\frac{d\bar{u}}{dt} = -\frac{\pi\rho d^2}{8m}\left(C_{D_o} + C_{D_{\alpha}2}\,\alpha_r{}^2\right)v\bar{v} + \frac{\pi\rho d^2}{8m}C_{L_{\alpha}}v^2\alpha_r -$$

$$\frac{\pi\rho d^3}{16m}C_{y_{p\alpha}}\,p(\alpha_r \times \bar{v}) - g_o\frac{R^2}{r^3}\bar{r} + 2(\omega \times \bar{u}) \tag{3.2a}$$

$$\frac{dp}{dt} = \frac{\pi\rho d^4}{16 I_x}pvC_{l_p} \tag{3.2b}$$

$$\alpha_r = -\frac{8pI_x}{\pi\rho d^3 C_{M_{\alpha}}}\frac{\left[\bar{v} \times (d\bar{u}/dt)\right]}{v^4\alpha_r} \tag{3.2c}$$

The quantities in the above equations are defined as follows:

$\bar{u} = \dfrac{d\bar{x}}{dt}$, $\quad \bar{v} = \bar{u} - \overline{W}$, $\quad \bar{r} = \bar{x} - \overline{R}$

$R = (0, - R, 0)$, [W denotes the wind vector]

$\omega =$ $(-\Omega\cos[\text{latitude}]\cos[\text{azimuth}],$

$-\Omega\sin[\text{latitude}],$

$\Omega\cos[\text{latitude}]\sin[\text{azimuth}]),$

where $\Omega = 7.29 \times 10^{-5}$ rad/s (rotation of earth),

R=6370320m (radius of earth),

$g_0 = 9.80665[1 - 0.0026373\cos(2 \times \text{latitude}) + 0.0000059[\cos(2 \times \text{latitude})]^2],$

The axis system used is as for the point mass model with $\bar{x}$ along the line of fire.

As may be seen from the above equations, the aerodynamic coefficient input required is extensive and accuracy of these aerodynamic coefficients is crucial for reliable estimates of range. However, for most artillery shells, the reliability of estimated values of aerodynamic coefficients is not higher enough to inspire confidence in resulting range estimates from this model. Further, because the equation for calculating yaw of repose assumes quasi-liner aerodynamics, the use of non-linear aerodynamics in equation is questionable[1].

3.4 Six Degrees Of Freedom Model (SDF)

The requirements needed for a trajectory model for predicting flight variables are that:

1) the trajectory be three- dimensional
2) provision be made for arbitrary wind velocity, azimuth and other meteorological conditions
3) non-linear aerodynamics with respect to flow incidence angle (angle of attack) be included.

The first two requirements are obvious since in the consideration of side winds and the effect of spin, the trajectory is three-dimensional and the wind velocity, azimuth and meteorological conditions are arbitrary. The third requirement is imposed because spinning shells during high angle launch (angle of launch > 45°) experience large angle of attack near vertex, which greatly exceeds the linear range of aerodynamic coefficients[15].

A trajectory simulation incorporating the above requirement is presented below.

$$\dot{u} = (\bar{q}\, s/m)C_x - qw + rv - g \sin\theta + Th/m \tag{3.3a}$$

$$\dot{v} = (\bar{q}\, s/m)C_y - ru + pw + g \sin\phi \cos\theta \tag{3.3b}$$

$$\dot{w} = (\bar{q}\, s/m)C_z - pv + qu + g \cos\phi \cos\theta \tag{3.3c}$$

$$\dot{p} = \bar{q}\, sbC_l + qr(I_y - I_z) / I_x \tag{3.4a}$$

$$\dot{q} = \bar{q}\, sbC_m + rp(I_z - I_x) / I_y \tag{3.4b}$$

$$\dot{r} = \overline{q}\, sbC_n + pq\,(I_x - I_y)\,/I_z \tag{3.4c}$$

$$\dot{\phi} = p + q \tan\theta \sin\phi + r \tan\theta \cos\phi \tag{3.5a}$$

$$\dot{\theta} = q \cos\phi - r \sin\phi \tag{3.5b}$$

$$\dot{\psi} = r \cos\phi \sec\theta + q \sin\phi \sec\theta \tag{3.5c}$$

To drive the spatial position equations, above equation were used to transform the body-axis velocity (u, v, w) into earth-fixed-axis. The equations are:

$$\dot{X} = u \cos\psi \cos\theta + v(\cos\psi \sin\theta \sin\phi - \sin\psi \cos\phi)$$

$$+ w(\cos\psi \sin\theta \cos\phi \quad \sin\psi \sin\phi) \tag{3.6a}$$

$$\dot{Y} = u(\sin\psi \cos\theta) + v(\sin\psi \sin\theta \sin\phi + \cos\psi \cos\phi)$$

$$+ w(\sin\psi \sin\theta \cos\phi - \cos\psi \sin\phi) \tag{3.6b}$$

$$\dot{Z} = u \sin\theta - v \cos\theta \sin\phi - w \cos\theta \cos\phi \tag{3.6c}$$

Aerodynamic model used in this analysis is as given below:

$$Cx = -C_{Dwind} \cos\alpha \cos\beta + C_L \sin\alpha - Cy_{wind} \cos\alpha \sin\beta \tag{3.7a}$$

$$Cy = Cy_{wind} \cos\beta - C_{Dwind} \sin\beta \tag{3.7b}$$

$$Cz = -C_L \cos\alpha - C_{Dwind} \sin\alpha \cos\beta - Cy_{wind} \sin\alpha \sin\beta \tag{3.7c}$$

where

$$C_L = C_{Lo} + C_{L\alpha}\alpha + C_{Lq}(qd/2v) + \eta C_{dc}\left(\frac{Sp}{Sref}\right)\mathrm{Sin}^2\alpha\mathrm{Cos}\alpha - C_{do}\mathrm{Cos}^2\alpha\mathrm{Sin}\alpha \tag{3.8a}$$

$$Cy_{wind} = Cy_o + Cy_\beta\beta + Cy_r(rd/2v) \tag{3.8b}$$

$$CDwind = Cd \tag{3.8c}$$

$$Cl = Clp(pd/2v) \tag{3.9a}$$

$$C_m = C_{mo} + C_{m\alpha}\alpha + C_{mq}\frac{qd}{2V} + \eta C_{dc}\left(\frac{Sp}{Sref}\right)\left(\frac{X_{cg} - X_p}{d}\right)\mathrm{Sin}^2\alpha \tag{3.9b}$$

$$C_n = C_{no} + C_{n\beta}\beta + C_{nr}\frac{rd}{2v} \qquad (3.9c)$$

wind model used in this analysis is as given below :

$$u' = u - W_x \cos\theta \cos\psi - W_y \cos\theta \sin\psi + W_z \sin\theta \qquad (3.10a)$$

$$\begin{aligned} v' = v &- W_x (\cos\psi \sin\theta \sin\phi - \sin\psi \cos\phi) \\ &- W_y (\cos\psi \cos\phi + \sin\psi \sin\theta \sin\phi) \\ &- W_z (\cos\theta \sin\phi); \end{aligned} \qquad (3.10b)$$

$$\begin{aligned} w' = w &- W_x (\cos\psi \sin\theta \cos\phi + \sin\psi \sin\phi \\ &- W_y (\sin\psi \sin\theta \cos\phi - \cos\psi \sin\phi) \\ &- W_z \cos\theta \cos\phi ; \end{aligned} \qquad (3.10c)$$

Thus $\alpha = \mathrm{atan}(w'/u')$ and $\beta = \mathrm{atan}(v'/u')$

where W_x, W_y, W_z are the wind component blowing toward the x,y and z directions

However, the in determinability of many initial conditions and unavailability of reliable estimates of aerodynamic coefficients, which are required as inputs, results in model not giving desired results. The sensitivity of the variation of aerodynamic coefficients to range and drift prediction using mathematical model is illustrated in Chapter 4.

3.5 Generation of Simulated fired and Radar Tracked Data

Due to non-availability of fired data (range and drift) and radar tracked data (x, y, z) of artillery shell in varying wind conditions, simulated data were generated solving six-degrees-of-freedom equations of motion as given in Eqs. 3.3 to 3.11. These equations were solved using fourth order Runge-Kutta method for solving simultaneous differential equations. Various wind profiles, having head/tail and cross wind components were used as input to the trajectory model. A typical wind profile used for data generation is presented in Fig. 3.1. The mass, moment of inertia characteristics,

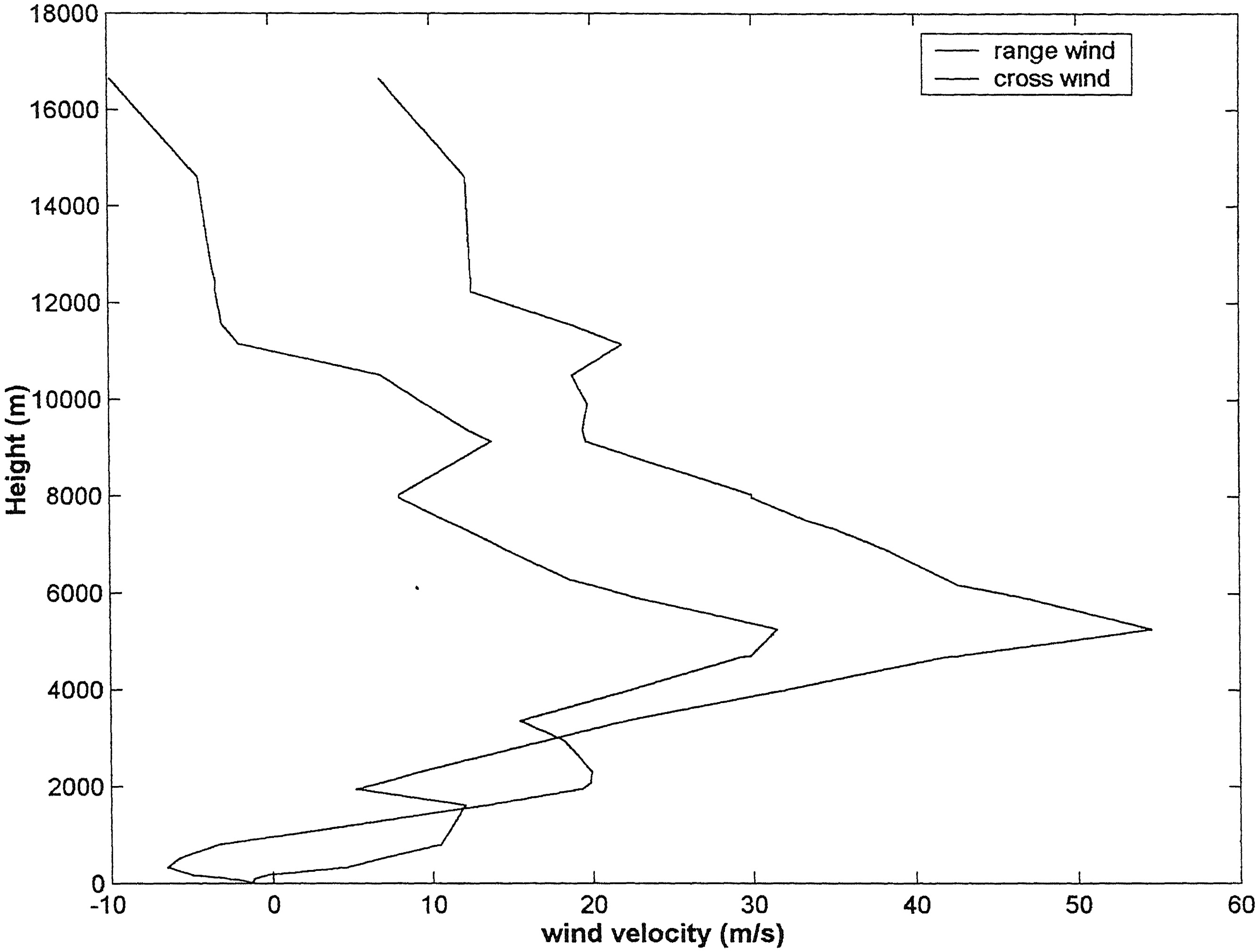


Fig 3.1 wind distribution of a variable wind profile as a function of height

aerodynamic coefficients and launch velocities of 155mm Bofors shell supplied by Armament Research and Development Establishment (ARDE) Pune, were used to compute the trajectory elements like range, drift etc. Range is the distance covered by the shell along the line of fire, whereas the drift gives the measure of lateral deviation from the line of fire. The computed range and drift data for different elevations under varying wind conditions (as given in Fig. 3.5) obtained using SDF model will be termed as Measured Range/Drift data for further reference. However, the trace of the spatial path of the center of gravity of the projectile (x, y, z) computed using SDF model will be referred to as Radar Tracked Data.

3.6 Range Tables for B-Shell

As mentioned earlier, due to non availability of real firing data, the range tables for the 155mm Bofors shell HE 77B (here after referred to as B-shell for convenience) are used for the present study. These tables were supplied by ARDE, Pune. The range table lists range obtainable for various firing table elevations (hereafter referred to as firing angle, θ) under standard calm atmospheric conditions and for nominal values of weight and muzzle velocity. Also time of flight and correction to bearing drift is provided. The corrections to these listed values of range for each value of θ due to following variations at the time of firing are also provided:

1) Variations in ambient atmospheric conditions (temperature, density)
2) Head/tail wind
3) Crosswind
4) Change in weight and muzzle velocity from the corresponding nominal value.

The range tables have been prepared using the modified point mass trajectory model. As pointed out earlier, this model suffers from a few limitations, mainly because of the not-so-reliable accuracy of aerodynamic coefficients that need to be used to solve the equations of motion. The complete six-degree-of-freedom model would also suffer for the same reasons. Even if accurate aerodynamic coefficients were available, there are few

other uncertainties that would affect the range estimates in real life and cause dispersion of shells. A few such uncertainties are briefly outlined below:

1. Slight differences between nominally similar projectiles

Any differences in mass, shape, surface finish, etc., will cause changes in the trajectory of the projectile to some extent. Projectiles might suffer from two types of asymmetries while passing through the manufacturing stage: Configurational asymmetries and inertial asymmetries. The inertial asymmetries may be of mass unbalances wherein center of mass is not on the geometrical axis of symmetry and dynamic unbalance where the principal axis of inertia is not collinear with this axis. These asymmetries can lead to large dispersions, and it is by keeping manufacturing tolerances to minimum, and by imparting some amount of spin that one can reduce the dispersion due to this effect. However, spin rate is to be carefully chosen to avoid the spin-yaw resonance zone.

2. Meteorological conditions

It is noted that the solution of equations of motion uses a single value for head or tail wind and crosswind. Furthermore, the corrections to the range (tabulated for standard atmospheric conditions) for variation in temperature and density are incorporated by using a single value of temperatures and density at the location of firing. It is realized that the shell will be passing through different wind and atmospheric conditions of temperature and density as its altitude varies during its in-flight trajectory. However, for the purpose of applying corrections, a weighted mean value of wind velocity, temperature and density is used to account for varying conditions prevailing at different altitudes.

3. Variable launch conditions: Variation in muzzle velocity, gun-jump and throw-off, initial yaw, etc.

At the time of shell leaving the gun barrel, the initial conditions experienced by the shell are not identical for all the shells. In particular, the initial velocity of shell (muzzle velocity) depends upon the charge concentration at the time of firing.

For the spun projectiles crosswind has an effect in the vertical plane due to the time taken to adapt to the air-relative zero yaw position. This occurs whenever the projectile emerges into a region of significantly different wind-relative zero yaw attitude, but most commonly has its effect on a projectile exiting from the launcher. Unlike the downward carry effect, which is usually roughly quadratic in range and depends on the wind at all points down-range, this effect is called aerodynamic jump, which is linear in range and dependent on wind at one point. There is a similar term due to the transverse component of a head wind. The total effect is called windage jump.

The initial yaw and yawing rate of a projectile will obviously determine to a large extent what yaw levels are present in the early stage of the trajectory. Furthermore, if the damping is poor, they may lead to consistently high yaw and thus cause dispersion in range due to yaw drag, especially with indirect fire munitions.

3.7 The Neural Models

The limitations of the mathematical models so far used for predicting range of artillery shells motivated us to look at an alternative approach to modeling. The feed forward neural network provides one such potential way of modeling. The neural model needs identification of suitable input-output variables to map the relationship existing between them. The functional relations is obtained by training with measured input-output variables and then the trained network is used to predict the output for a set of inputs not seen by network during the training phase. The measured range/drift data will be used to train neural network for range modeling, and the radar tracked data will be

used to train neural network for trajectory modeling and prediction. For the purpose of developing neural model, data generated from these sets six-degrees-of-freedom model are randomly selected to form sets having chosen number of data points. One of these sets is used for training the network. Then two sets of data points, are taken for validations sets, which are different from the training set. These two sets are used to verify the acceptability of the trained network. As mentioned in the Appendix A, the acceptability of the network architecture is decided by comparing the MSE during training phase and validation phase. The thumb rule applied is that MSE for the two validation sets should not be greater than about two or three times the MSE for the training set. Of course, the MSE permitted on the training set is prescribed and kept below it, while choosing the architecture of the network, i.e., while choosing the learning rate, the momentum rate, the number of iteration, the number of neuron, etc. Finally, one set of data not used for the above two stages of training or validation is used to predict the required output. This output is compared with the known output corresponding to the same inputs, and thus shows acceptability of the neural model in predicting the required output variables.

From application point of view, the following four types of modeling problem are taken up for study. The neural network modeling for these four cases are presented in details in the next chapter along with the results obtained via each of these models. However, a brief outline of the three models is given below.

MODEL 1

This model deals with the problem of predicting range and drift experienced by artillery shells while traversing under varying wind conditions. The output variables of neural model would depend on elevation θ, and varying wind W_x, W_y as function of height. No scheme could be evolved to map elevation and varying wind to range and drift. To overcome this difficulty equivalent constant wind (ECW) for each elevations[2] were computed and were used as input along with elevation to establish neural modeling between input and output.

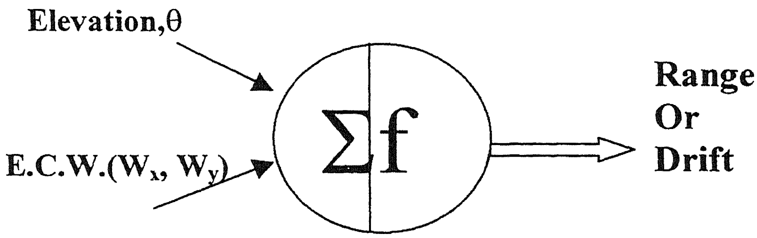


Fig. 3.2 Schematic representation of FFNN for Model 1

MODEL 2

This neural model makes an attempt to improve the prediction capability of Model 1 by implicitly incorporating not only the effect of varying wind as function of height but also as a function of axial distance from the point of launch. Here, the input pair will include θ, ECW at launch site (as function of height only), and the output will have measured range or drift experienced by the shell when fired under such wind conditions.

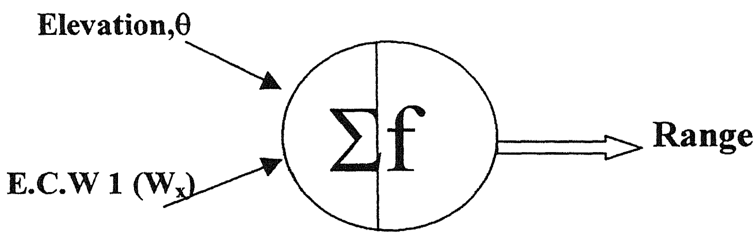


Fig. 3.3 Schematic representation of FFNN for Model 2

MODEL 3

A group of shells fired under similar launch and environmental conditions produces different values of range and drift due to associated uncertainties with variation in mass, shape, muzzle velocity, gun jump and throw-off etc.[1] For real life applications mean point of impact (MPI) is computed by taking the average on the values of range and drift separately achieved by different shells fired under similar conditions. The proposed model uses elevation as input and measured mean point of impact as output for neural

modeling. This model can be used to improve prediction capability as it is expected that the neural mapping would take into account the effects of uncertainties in range and drift implicitly when it is trained measured with MPI data.

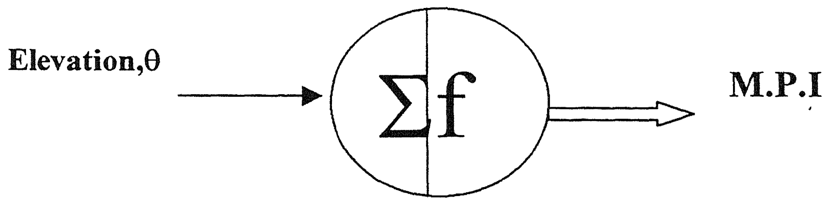


Fig. 3.4 Schematic representation of FFNN for Model 3

MODEL 4

The neural models available [14] so far have the capability to predict a single value for range and drift for different elevations. These models cannot be used to predict the trajectory (spatial path) followed by the shell. Model 4, proposes a scheme using neural mapping to predict trajectory traversed by projectile when fired under varying launch and meteorological conditions. The input will consist of elevation, spatial location of the center of gravity along the x-direction and prevailing wind velocities. The neural output will consist of height or drift of the center of the gravity of the projectile. The scheme proposed via Model 4 can be used to train and predict the trajectory of artillery shells using radar tracked data.

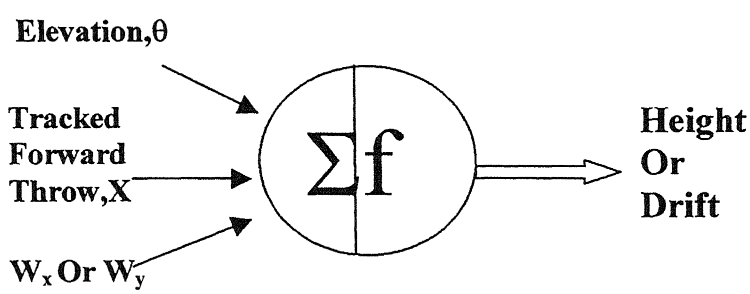


Fig. 3.5 Schematic representation of FFNN for Model 4

The results and discussion of all the models along with details of modeling are presented in the next chapter.

CHAPTER 4
CONVENTIONAL MODELS NEURAL MODELS RESULTS AND DISCUSSIONS

In this chapter, we first compare the prediction capability of the various conventional models like, PM, MPM and SDF model. To start with, range and drift for different elevations under standard atmosphere were computed using all the three trajectory models and the results were compared with the range table values. Based on the above study, SDF model was chosen for further trajectory analysis. Further to improve the prediction capability of the SDF model, the effect of high angle of attack in lift forces and pitching moments was incorporated in SDF model and range and drift were predicted and compared with range table values In order to estimate the sensitivity of the results obtained through SDF model with respect to variations in estimates of aerodynamic coefficients, the trajectory model was run for various combinations of varied aerodynamic coefficients Finally, details of all the neural models along with the results are discussed in this chapter.

4.1 Comparison of Prediction Capability of Point-Mass, Modified Point-Mass and Six-Degrees-of-Freedom Model

All the conventional models, were run to predict range and drift under standard atmosphere for various elevations (88.4 mils to 1243.5 mils). Table 4 1(a) and (b) present the values of range and drift obtained for various elevations respectively. Referring Table 4 1(a), it can be observed that ranges obtained by using SDF model lie close to range table values however drifts of the shell predicted by the SDF model as given in Table 4.1(b) are not as good as expected. It may be noted that the PM model did not produce any estimate for drift. The drift is because of spin, and since PM model doesn't incorporates effect of spin in its equations of motion, therefore no drift was predicted by this model. The results obtained are also presented graphically in Fig 4.1(a) and (b) MPM model also predicted range and drift accurately. However, due to assumption of quasi-linear aerodynamics for calculating angle of yaw, this model was not used for

Table 4.1 Comparison of Prediction Capability of PM, MPM and SDF Models.

(a) Range

Elevation Mils	Range (Range Table (m)	Range SDF (m)	Range PM Model(m)	Range MPM. Model(m)
88 4	8000	7960 2	8006.1	7909 2
175 1	12100	12607	12143	12013
265 1	14900	14870	14966	14813
354 0	17100	17073	17154	17009
446 4	19000	18977	19065	18906
534 2	20500	20482	20583	20404
621 6	21700	21688	21784	21604
710.9	22600	22596	22693	22505
802 3	23100	23106	23209	23009
884.1	23100	23115	23232	23012
976 1	22500	22523	22666	22419
1066.8	21200	21224	21395	21133
1154 0	19200	19193	19459	19177
1243.5	16300	16110	16713	16411

(b) Drift

Elevation	Drift (Range table)(m)	Drift Six-D-of-freedom(m)	Drift Point mass Model(m)	Drift Mod. Pm. Model(m)
88 4	29 06	30.359	0	29.829
175.1	84 341	89.737	0	88.055
265 1	144.81	155 98	0	153.6
354 0	211.52	228 09	0	224.51
446 4	285.37	310.35	0	304.94
534.2	362 23	395 18	0	387.42
621 6	445 19	487 07	0	475.89
710.9	541 27	592 03	0	575.13
802 3	662 03	720 61	0	693.16
884 1	788.9	855.95	0	814 07
976 1	951 48	1028.6	0	964.58
1066 8	1114 6	1196.5	0	1111.1
1154 0	1266 7	1329	0	1246
1243 5	1404 7	1297.9	0	1373.1

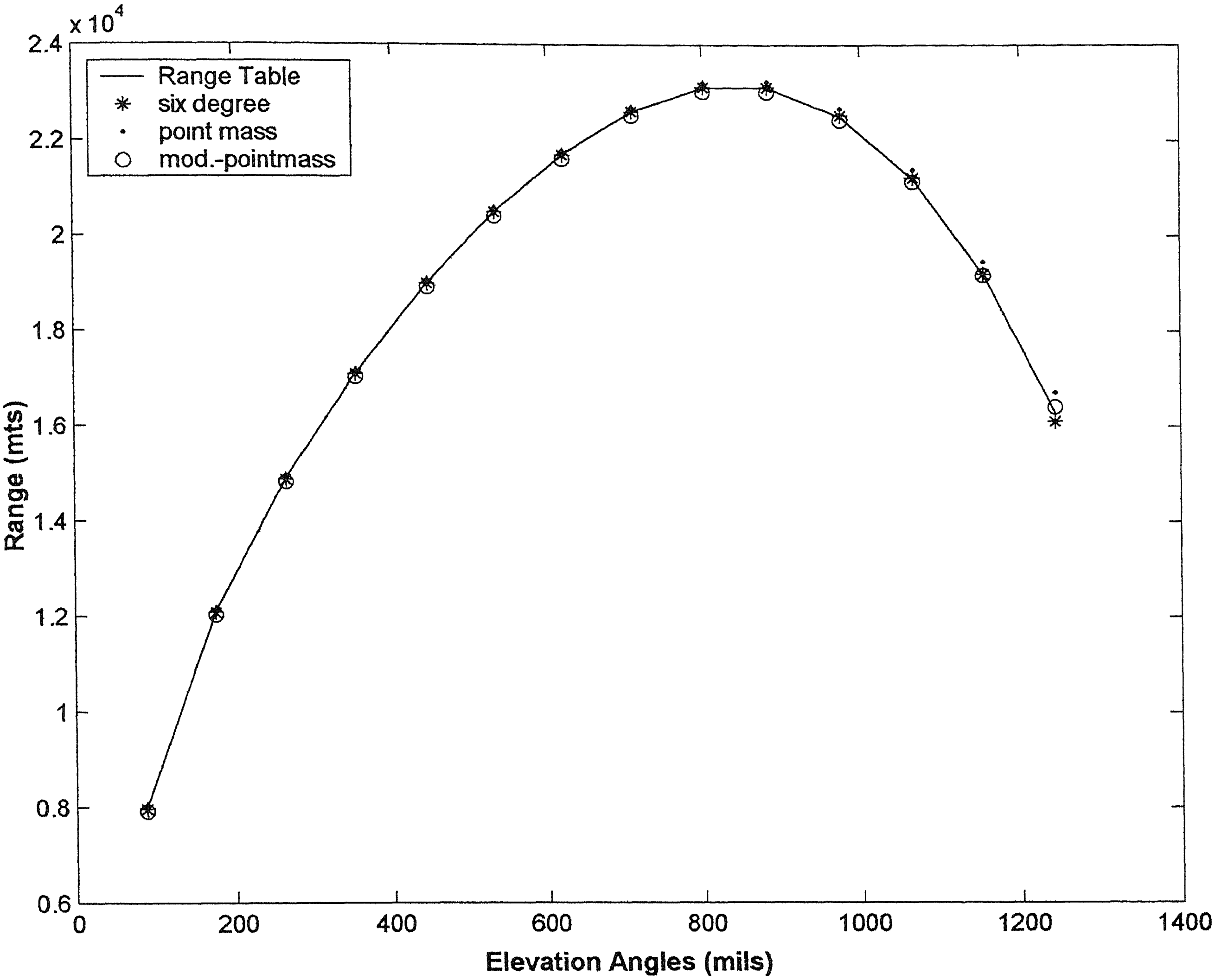


Fig. 4.1 Comparison of Prediction Capability of PM, MPM and SDF Models
(a) Range

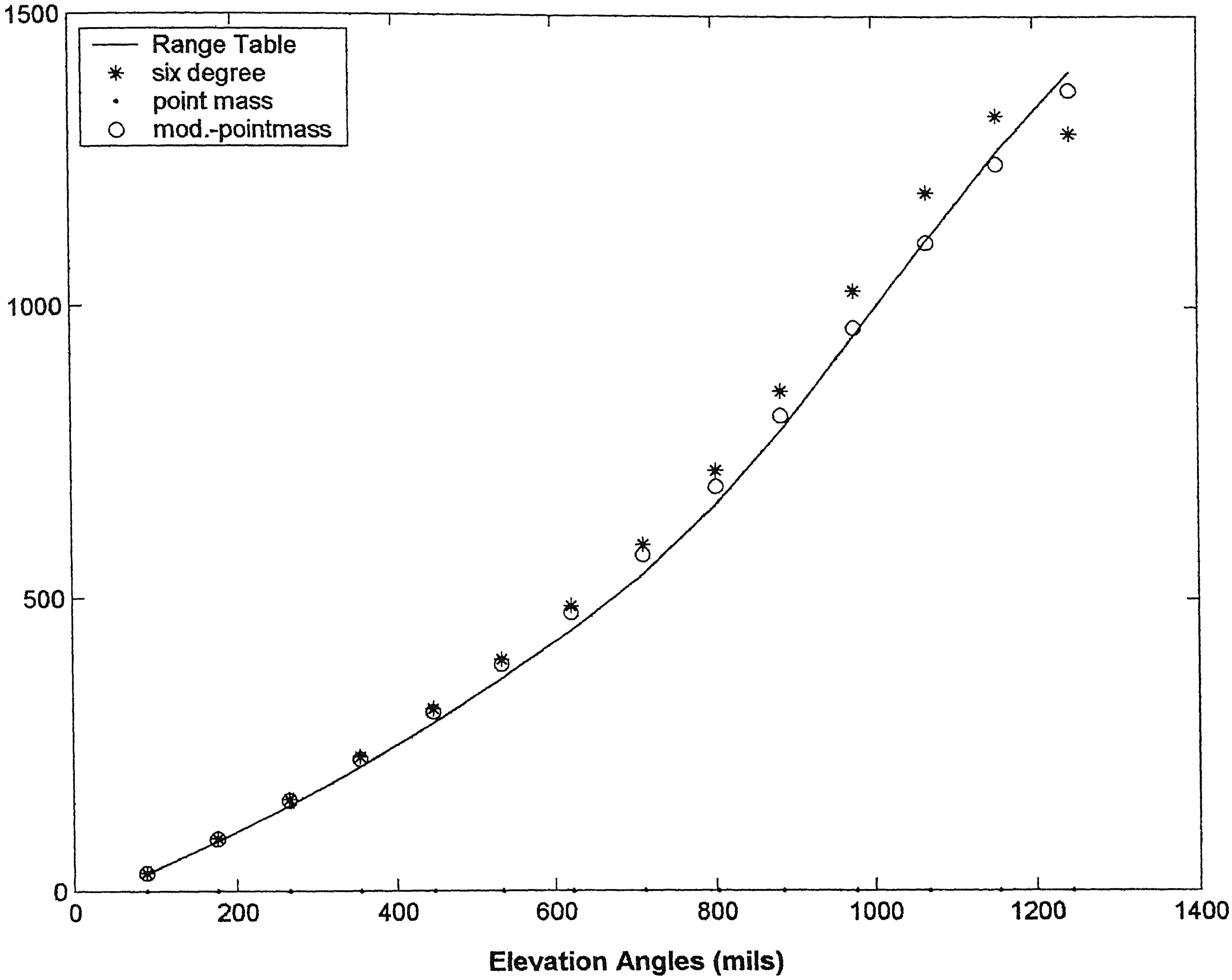


Fig. 4.1 Comparison of Prediction Capability of PM, MPM and SDF Models
(b) Drift

further analysis Based on this study, six-degrees-of-freedom model was selected for further applications.

4.2 Prediction of Range and Drift of Artillery Shell Fired at Different Elevations in Presence of Constant Head/Tail, Cross Wind

For artillery shell, head and tail wind decreases or increases the range respectively The cross wind deviates the shell along the direction of wind It contributes toward the deviation of the shell from the line of fire.

The SDF model was run for predicting range and drift under constant winds of 5,10 and 20 m/s at various elevations Column 2, 3 and 5 of Table 4.2 respectively present the values for range or drift as given in range table Referring Table 4 2(a) and (b) and comparing prediction values with range table values, it can be seen that the SDF model predicted the range and drift quite satisfactorily A closer look at the data reveals that the predictions in drift are inferior as compared to range predictions. It may be mentioned here that the aerodynamic coefficients used for running the SDF model were supplied by the manufacturer. These coefficients were frozen at design and evaluation stage after calibrating the trajectory model using exhaustive fired data. The trajectory model used by the manufacturer was the modified point-mass model. However it is practically impossible to arrive at exact values of these aerodynamic coefficients The inferior quality of drift prediction is attributed to unreliable estimates of aerodynamic coefficients namely Clp, Cn_{β} etc.

4.3 Effect of Variation of Aerodynamic Coefficients in Range and Drift.

Accurate numerical values of the aerodynamic coefficients are of paramount importance for predicting range and drift through the conventional mathematical models (trajectory models) In order to study this effect the values of various aerodynamic coefficients, were varied and corresponding range and drift were computed for a given elevation For this study the values of drag coefficient (C_d), lift coefficient (C_L), moment coefficient (C_m) and the roll-damping coefficient (C_{lp}) were varied upto 20% in a step of 5% The elevation chosen was 1066.8 mils and the atmosphere chosen was standard atmosphere. Referring Table 4 3(a) it can be observed that a mere change of 1% in values

Table 4.2 Prediction of Range and Drift of an Artillery Shell Fired at Different Elevation in Presence of Constant Head/ Tail, Cross Wind.

(a) Range

Elevations (mils)	Range 5m/s (Table)	Range 5m/s 6D	Range 10m/s (Table)	Range 10m/s 6D	Range 20m/s (Table)	Range 20m/s 6D
802 3	23399	23404	23698	23701	24296	24294
1066 8	21505	21530	21810	21836	22420	22442
1154 0	19491	19485	19782	19776	20365	20351

(b) Drift

Elevations (mils)	Drift 5m/s (Table)	Drift 5m/s 6D	Drift 10m/s (Table)	Drift 10m/s 6D	Drift 20m/s (Table)	Drift 20m/s 6D
802 3	864.94	913.89	1067.6	1106.4	1473.5	1489.2
1066 8	1356 2	1422.8	1596 1	1648.3	2077.1	2096.7
1154 0	1517.5	1563.7	1765.1	1797.1	2262.1	2261 3

of C_d changes the range by around 140 m Generally the estimates of C_d at best could be obtained within 5% Thus the error in predicting range due to unreliable estimates of C_d alone could contribute to an error of 700 m, which is quite high and not acceptable from accuracy point of view The effect of variation of other coefficients C_l, C_m,C_{lp} on range is marginal Fig 4 2 confirms the above observations. The effect of variation of C_d C_L, C_m and C_{lp} on drift is presented in Table 4 3 (b) It may be mentioned that it is extremely difficult to estimate values of C_{lp} for bodies of revolution The error in estimating C_{lp} may be of the order of 50%. Thus, this alone will make substantial effect on drift prediction

4.4 Range and Drift Prediction using Varying and Equivalent Constant Wind

For real life applications conventional artillery users prefer to have firing tables (Range table) giving information about correction to be employed to launch angles based on equivalent wind. In order to asses the accuracy in predicting the effect of wind six-degrees-of-freedom model was run to predict range and drift using equivalent wind. Due to non-availability of measured range and drift data under varying wind condition , fired data were simulated using six–degree-of-freedom model with varying wind velocities as explained in Chapter 3. Wind profiles, as given in Fig. 3.1 was selected and range and drift were computed using trajectory model Next, the same trajectory model was run using ECW. Equivalent constant wind was computed using following weighting procedure as given in Ref 2

$$V_R = \sqrt{\left[\frac{\sum(W_x)}{n}\right]^2 + \left[\frac{\sum(W_y)}{n}\right]^2} \qquad 4.1(a)$$

$$\theta_R = \tan^{-1}\left[\frac{\sum(W_y)}{\sum(W_x)}\right] \qquad 4\ 1(b)$$

$$ECWx = V_R Cos(\theta)$$

$$ECW_y = V_R Sin(\theta)$$

Table 4.3 Effect of Variation of Aerodynamic Coefficients in Range and Drift

(a) Range

% Change in Coeff.		0	5	10	15	20
Range(m)	C_d	21180	20477	19829	19229	18671
	C_l	21180	21173	21165	21157	21149
	C_m	21180	21186	21192	21197	21201
	Cl_p	21180	21179	21178	21178	21177

(b) Drift

% Change in Coeff		0	5	10	15	20
Range	C_d	1325.7	1295.3	1265.9	1237 4	1212.8
	C_l	1325.7	1395.2	1464 6	1534	1603.2
(m)	C_m	1325.7	1268.8	1216.6	1167.9	1122
	Cl_p	1325.7	1313.9	1302.5	1291.5	1279.8

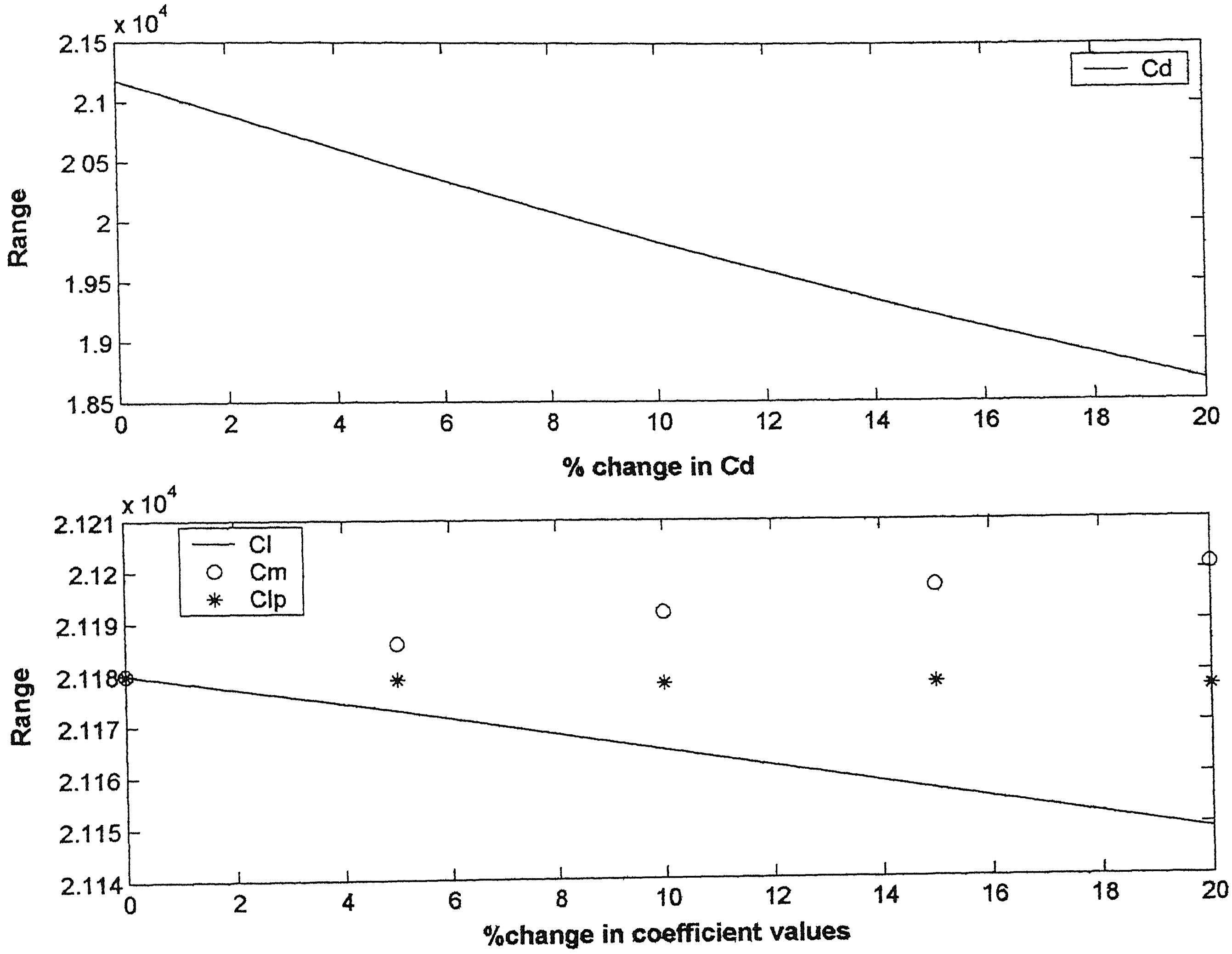


Fig 4.2(a) Effect of Variation of Aerodynamic Coefficients in Range

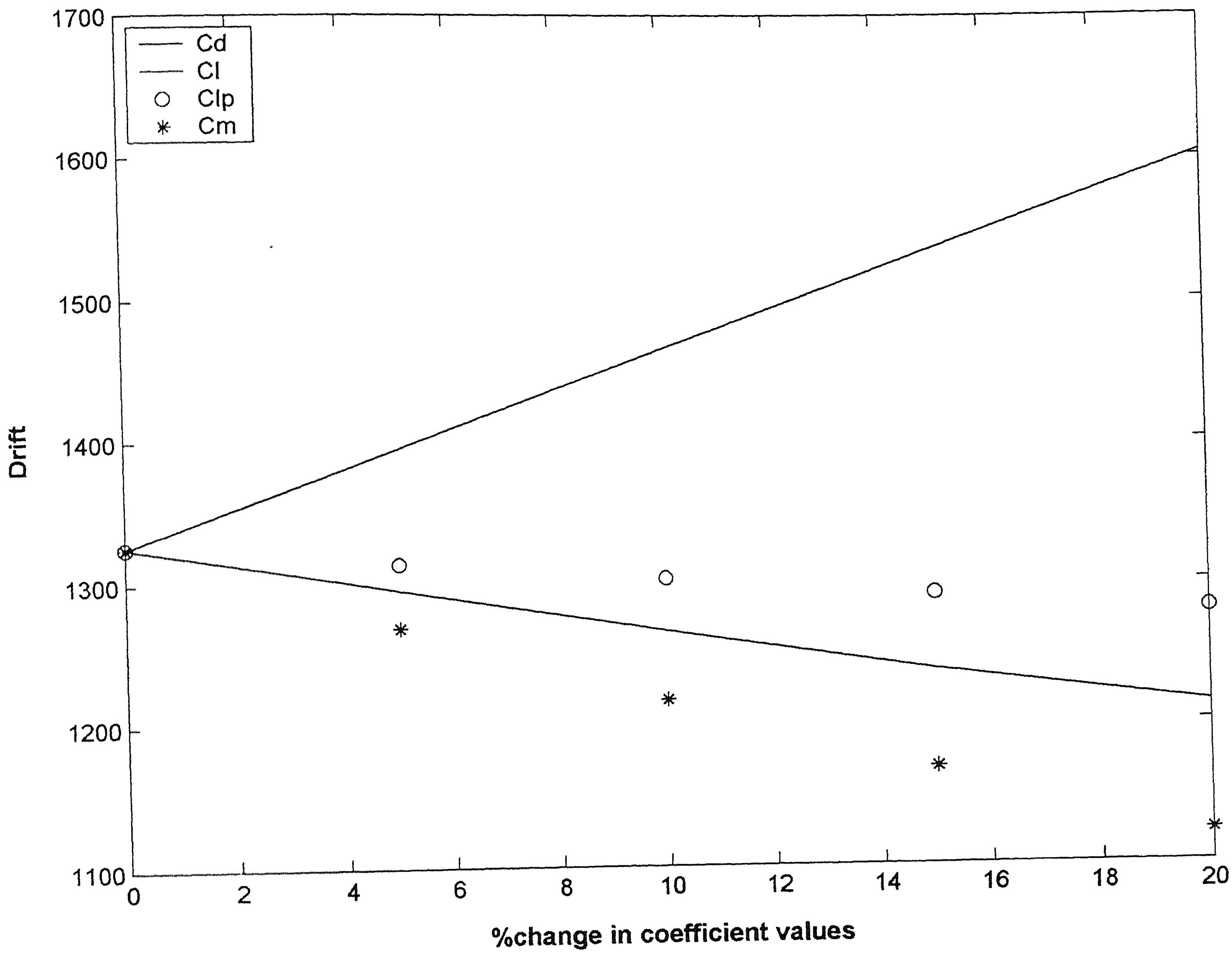


Fig 4.2(b) Effect of Variation of Aerodynamic Coefficients in Drift

Column 2 and 3 of a Table 4.4 (a) and (b) present the predicted values of range and drift using SDF model with varying and equivalent constant wind Based on these data range and drift values were computed using ECW for various elevations as presented in Table 4 4 (a) & (b) Referring Table 4 4, it can be stated that modeling varying wind using SDF model with ECW does not predict range and drift accurately However, this approach could be useful to get approximate measure of range and drift for the real life application. Similar observation is pictorially presented in Fig 4.3

4.5 Neural Modelling

MODEL 1

In model 1, we wish to develop neural model for predicting range and drift. These would, therefore, form the output variables depend on the firing angle θ and ECW (W_x, W_y)

Due to non-availability of real fired data for varying wind conditions, measured fired range/drift data as mentioned in Chapter 3 were used. It may be mentioned that the wind profile given in the Fig 3.1 was used for this case. The equivalent wind was computed using Eq (4.1) for different elevations. The input and output samples were randomly selected from these data. Although training was carried out for data sets having 100, 50 25 and 15 samples, the results for the most stringent case of data set having 15 samples are presented In addition two other samples of 30 samples each were generated for use as test data. The network tuning parameters were varied till acceptable network training achieved as per criteria set out in appendix A. Now a set of 10 samples, randomly taken from the data set, is used to predict range and drift. The results for the above are presented in Column 4 of Table 4.4 along with the results obtained using the SDF model in column 3 It may be observed that the predicted values from neural model are in good agreement with the measured/fired data. Figure 4.3 also depicts a comparison between the range and drift data obtained through neural model and SDF model using ECW Referring Table 4.4(a) and (b) and Fig 4 3 (a)and (b), it can be concluded that the use of ECW with neural model shows better promise as compared to SDF model in predicting performance of an artillery shell

Table 4.4 Range and Drift Prediction Using Varying and Equivalent Constant Wind

(a) Range

Elevation (mils)	Range		
	Actual (m)	Six Deg. with ECW (m)	Neural Net with ECW (m)
88 4	7943.4	8230.4	7936.8
175.7	11973	12648	11943
265 1	14850	15707	14830
354 0	17364	18136	17362
446.4	19403	20093	19408
534.2	21142	21592	21148
621.6	22632	22924	22629
710.9	23433	23751	23425
802.3	23856	24157	23872

(b) Drift

Elevation (mils)	Drift		
	Actual (m)	Six Deg. with ECW (m)	Neural Net with ECW (m)
88.4	29 695	37 972	31.058
175.7	142.71	135.94	144.06
265.1	288.15	265.33	286.53
354.0	373.85	425.26	377.61
446.4	600.51	651 17	601.78
534 2	902.13	874.88	899.49
621.6	1285.2	1306 4	1277.8
710.9	1552.1	1671 3	1553 0
802 3	1742.8	1980 8	1742 8

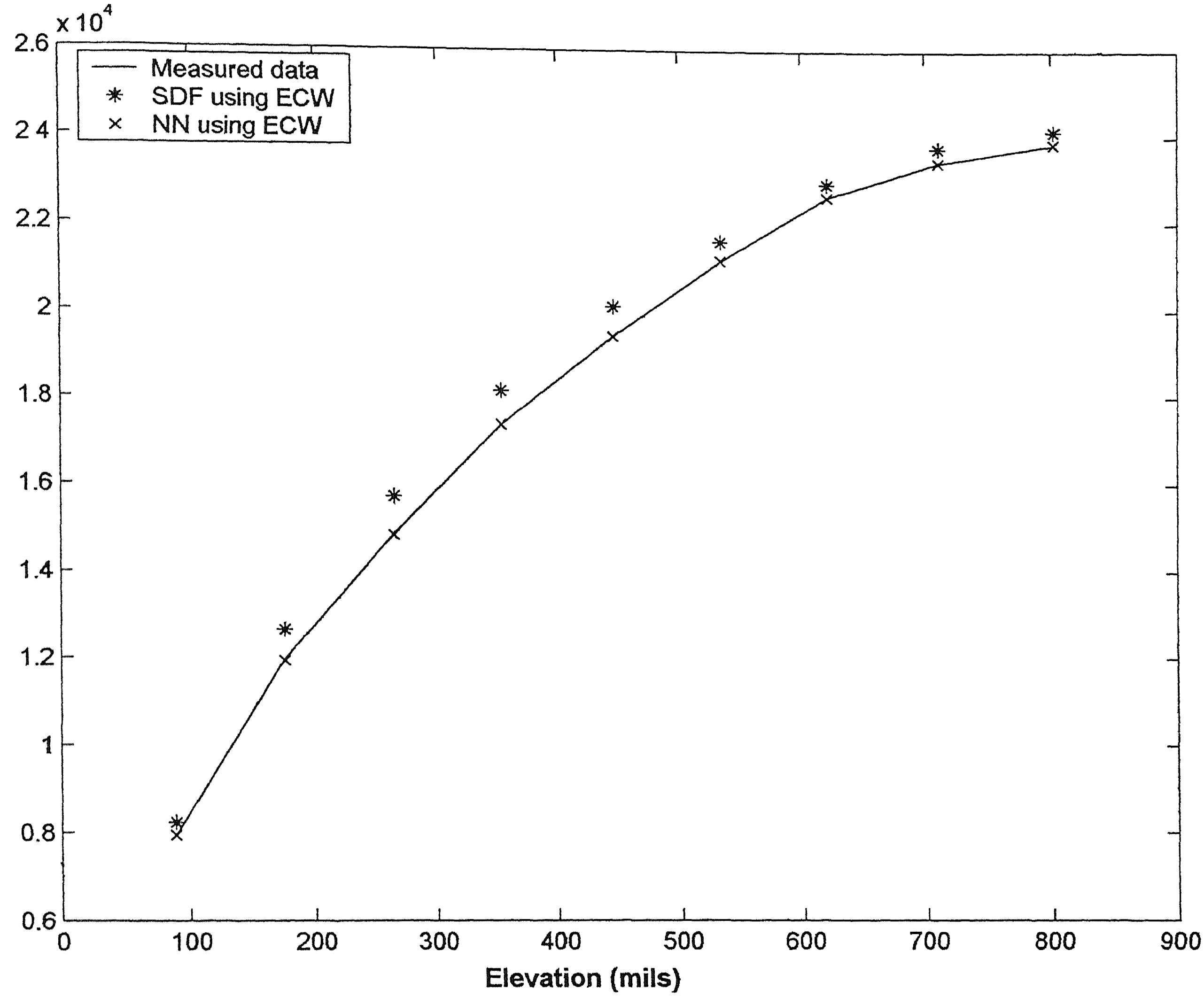


Fig 4.3 (a)Prediction of Range using SDF and neural Model 1 using ECW

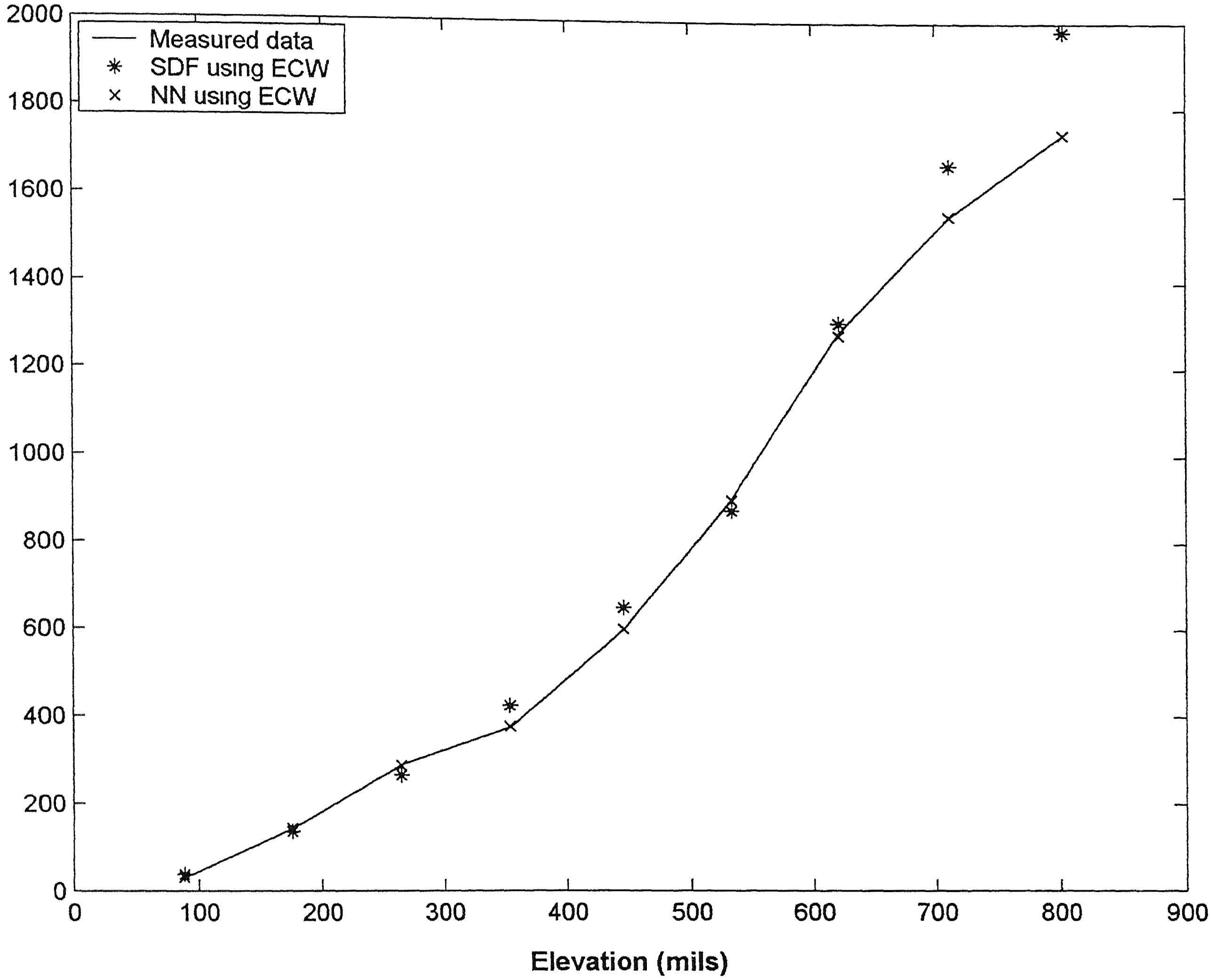


Fig 4.3(b) Prediction of Drift using SDF and neural Model 1 using ECW

MODEL 2

This model is prepared to enhance the performance prediction capability of neural modeling using ECW The need for this arises due to the fact that wind pattern at the point of launch and at the point of impact may be widely different. So this is an effort to predict the range and drift when the shell experiences widely different wind pattern as compared to the wind pattern at launch The conventional model under such circumstances would use the variable wind at launch to compute ECW The conventional model thus in no way would be able to incorporate the effect due to the prevailing wind at a far distance from the launch. In contrast neural models would be trained with actual fired data and hence the measured range and drift would have this effect implicitly incorporated into it. In other words, if exhaustive trial data for varying wind condition are used for training, the neural model would be able to implicitly map the relationship between two layers of wind profiles (if exists) in learning the architecture. Thus, this approach is expected to provide better results. To simulate the said wind condition, two wind profiles were used to calculate measured range and drift data at various elevations using SDF model. As stated earlier this data would be treated as measured data. The description of two wind profile used is given in Fig. 4.4. The neural model was trained with ECW (of the first layer) and θ as input and Range or drift as output. The predicted range for various elevations is presented in Table 4.5. It can be observed that as expected the neural model predictions are better than the prediction obtained through SDF model using ECW of first layer only. Figure 4.5 brings at the superiority of the neural model to the SDF model clearly.

MODEL 3

A group of shells fired under similar launch and environmental conditions produces different values of range and drift due to associated uncertainties with variation in mass, shape, muzzle velocity (mv), gun jump or throw-off[1]. For real life applications, mean point of impact is computed by taking the average of the values of range and drift achieved by different shells fired under similar conditions. Due to non availability of raw fired data, simulated fired data incorporating the effect of few uncertainity were

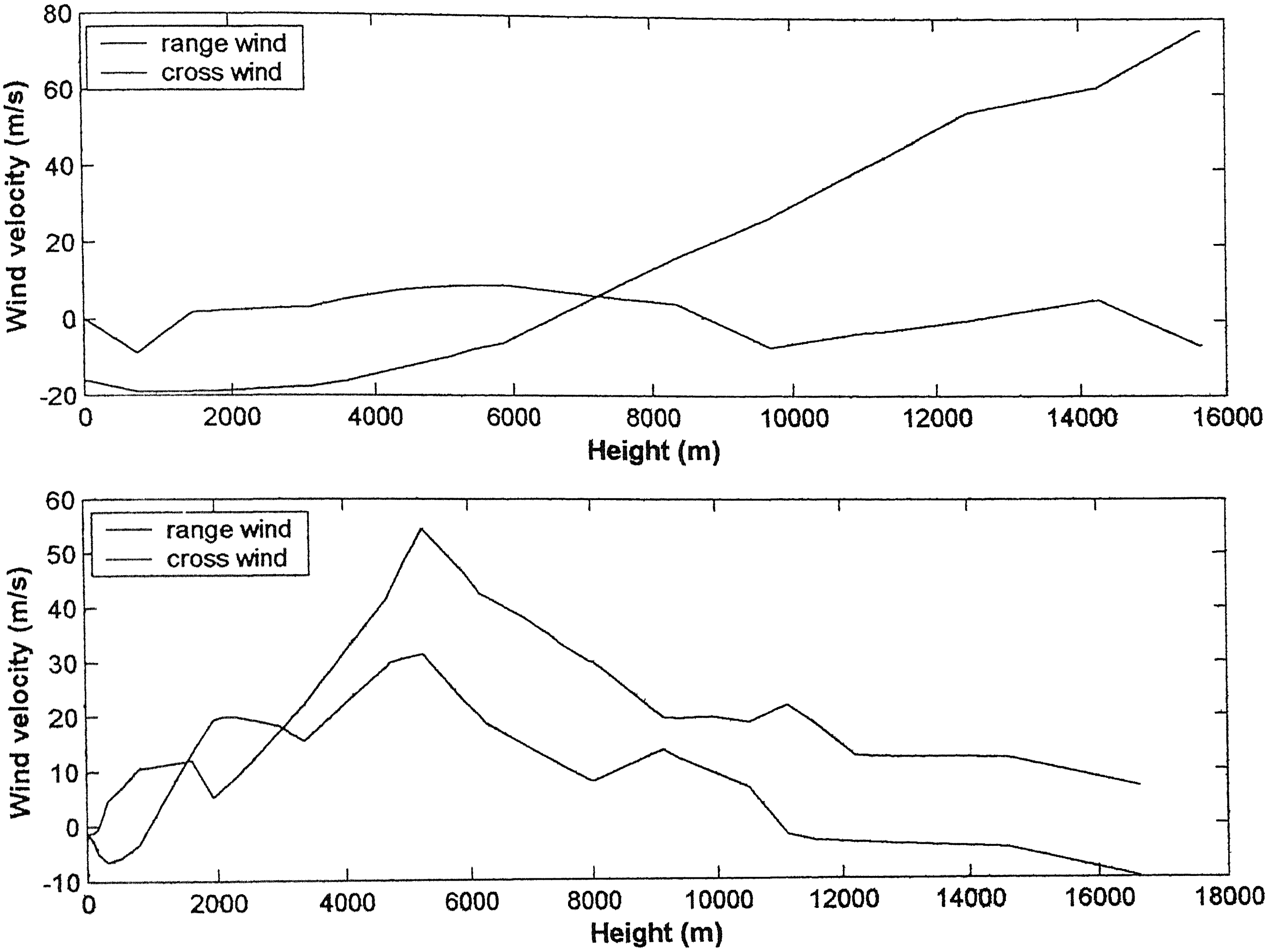


Fig. 4.4 Wind Profiles used to generate measured range/drift data

Table 4.5 Prediction of Range using Model 2

Elevations Mils	Range (m)		
	Measured	SDF using ECW1	NN using ECW1
88 4	7928	8230 4	7927 3
175 7	11911	12648	11915
265 1	14733	15707	14713
446 4	18862	20093	18861
534 2	20493	21592	20506
621.6	21955	22924	21929
710.9	22894	23751	22892
802 3	23544	24157	23544

Table 4.6 Prediction of MPI using Model 3

Elevations Mils	Range (m)		
	M.P.I.	M.P.I. Predicted by NN model	Range Predicted by SDF
20 6	2484.4	2471 2	2482.5
88 4	7973 7	7982 5	7960.2
131 9	10288	10286	10265
175.7	12100	12094	12067
220 3	13613	13613	13567
265.1	14926	14929	14870
291 6	15633	15636	15572
332 3	16641	16642	16573
354.0	17144	17145	17073
400 5	18153	18152	18075
446.4	19061	19061	18977
503	20070	20070	19980
568	21077	21077	20984
621 6	21781	21781	21688
666.6	22277	22277	22190

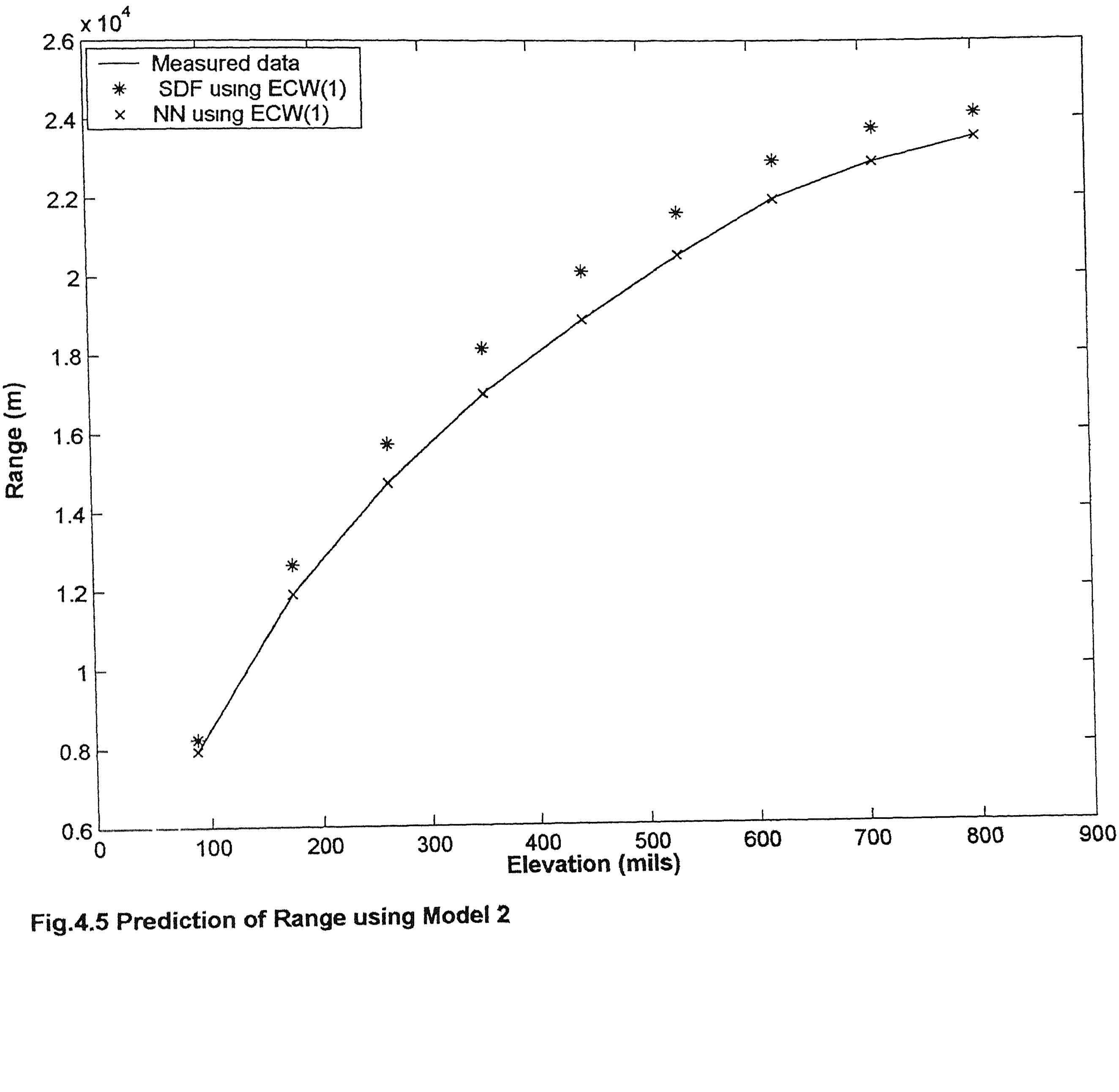


Fig.4.5 Prediction of Range using Model 2

generated using SDF model. For each chosen elevation four sets of randomly perturbed values of Cd and mv were used to generate four sets of simulated scattered range and drift data. This exercise was done for 33 elevations For each elevation, the mean of all the range values were obtained This mean value of range represents mean point of impact for a group of shells While preparing the data set, 16 sets of data out of 33 sets were used to train the neural networks and the remaining 17 were used for prediction As can be seen, from Table 4.6 the results of the predicted values matched fairly accurately with the measured M P.I Fig 4 6 pictorially brings out this comparison.

MODEL 4

So far, all the neural models described, were capable of predicting a single value for range and drift for different elevations These models don't have the potential to predict spatial coordinates (trajectory) of the traversing shell at different elevations. Through neural model 4, attempt has been made to predict the trajectory of shell when fired at different elevations under varying/constant wind environment. For validating the proposed model 4, the radar tracked data simulated through SDF model as explained in Chapter 3 (sec 3 5), were used To simulate varying wind profile, the profile as given in Fig 3 1 Chapter 3 was used. Around 15 sets of data were used for neural training. The neural network had θ, w_x or w_y, x as inputs and y(drift) and z(height) as output. During prediction phase, difficulty in forming the input file was encountered. For unknown θ, (for which the neural network needs to predict), the information of the z coordinate (height) of the shell trajectory under wind environment is not known apriori. Thus, difficulty in preparing input file for prediction. To overcome this difficulty, rigorous trajectory analysis were carried out with SDF model to study the effect of wind in shifting the z coordinates. The result of this study is presented in Fig 4.7. Referring Fig 4 7, it can be assumed that the variation in height (z coordinate) because of wind for most of the part of the trajectory is negligible. Thus, in the input file for prediction, the values of w_x or w_y. corresponding to height that the shell would have achieved in standard atmosphere were used Prediction for different elevations were obtained using this model. The predictions of trajectories corresponding to elevations of 30°, 45°, 65° and 70° are presented in Fig. 4 8 Referring this figure, it can be observed that the matching between

predicted height and tracked height is excellent For completion, the matching between the predicted and tracked height as function of elevations is presented in Fig 4 9.

The tuning parameters frozen for training neural models 1,2,3 and 4 are listed below for completion

The software platform used was Matlab R12

Model	No. of Hidden layer neurons	Learning Rate	Momentum Constant	Training Function	Learning Function	No of epochs
Model 1 (Range)	8	0.11	0 12	Trainlm	Logsig	500
Model (Drift)	8	0 11	0.12	Trainlm	Logsig	1000
Model 2	7	0 11	0 12	Trainlm	Logsig	700
Model 3	6	0 11	0 12	Trainlm	Logsig	3000
Model 4 (Height)	9	0 11	0 13	Trainlm	Logsig	4000
Model 4 (Drift)	8	0 12	0 12	Trainlm	Logsig	500

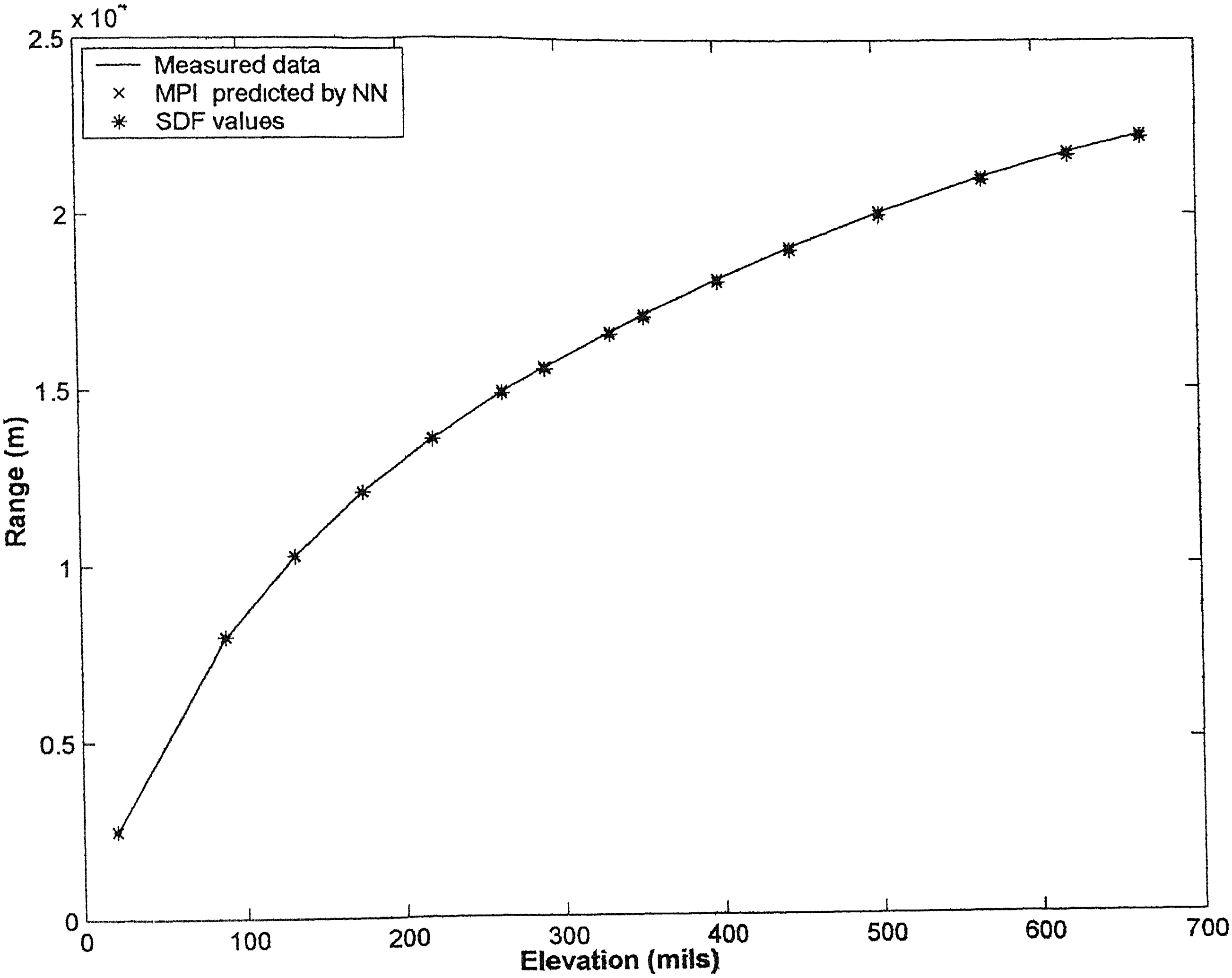


Fig. 4.6 Prediction of Mean Range using Model 3

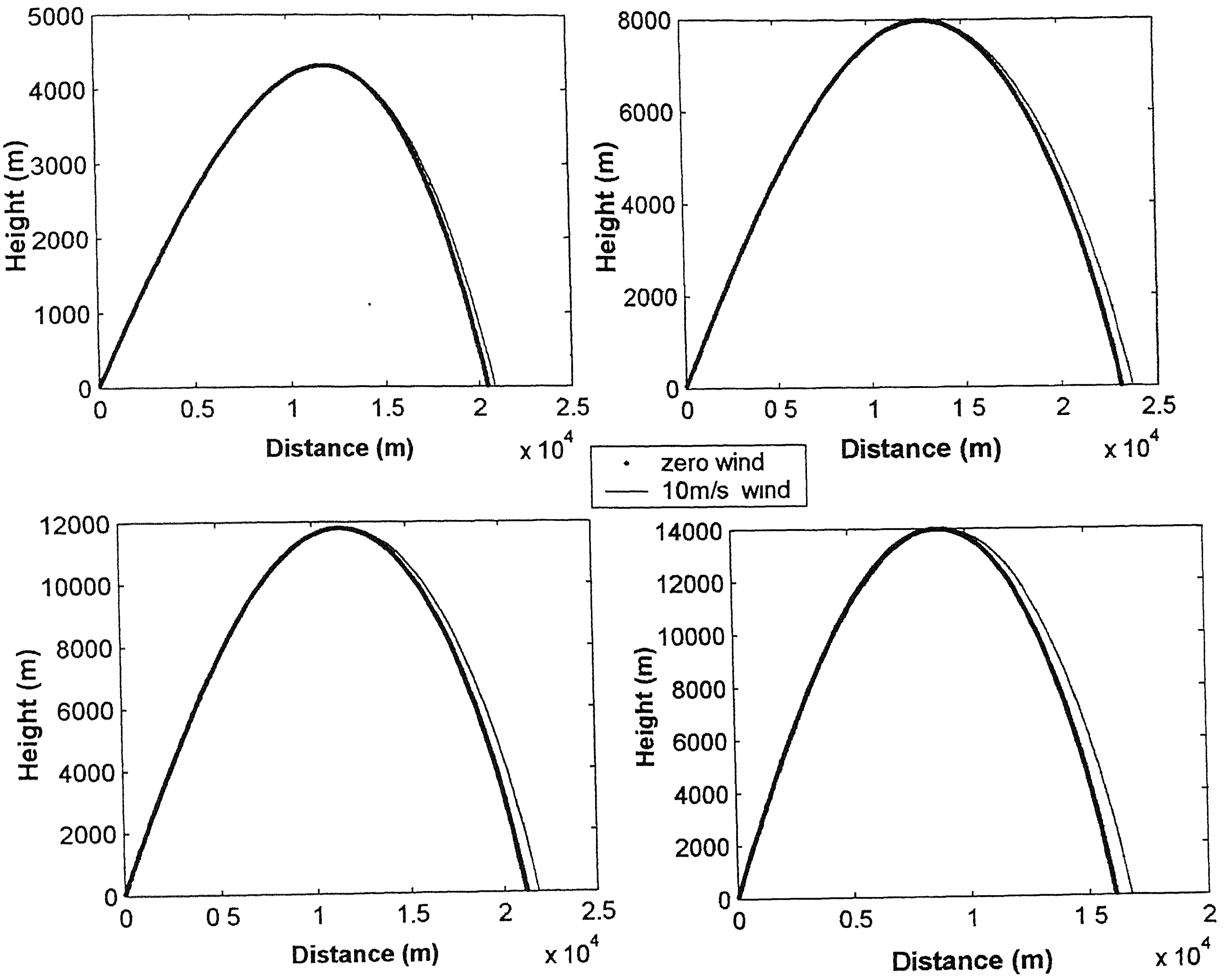
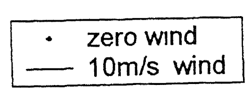


Fig. 4.7 Comparison of heights at no wind and 10m/s wind conditions for different elevations



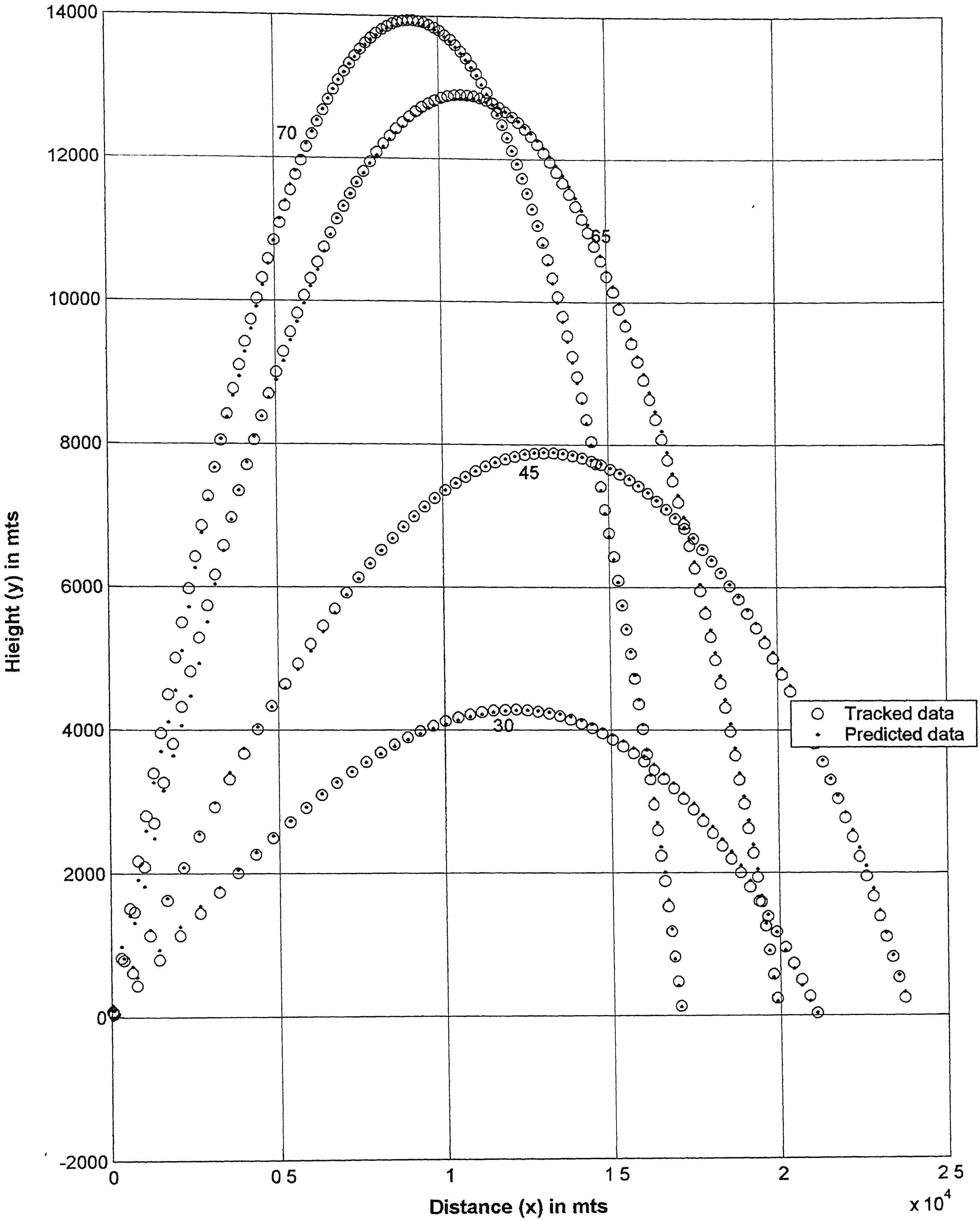


Fig 4.8 Trajectory prediction for some elevations using neural Model 4.

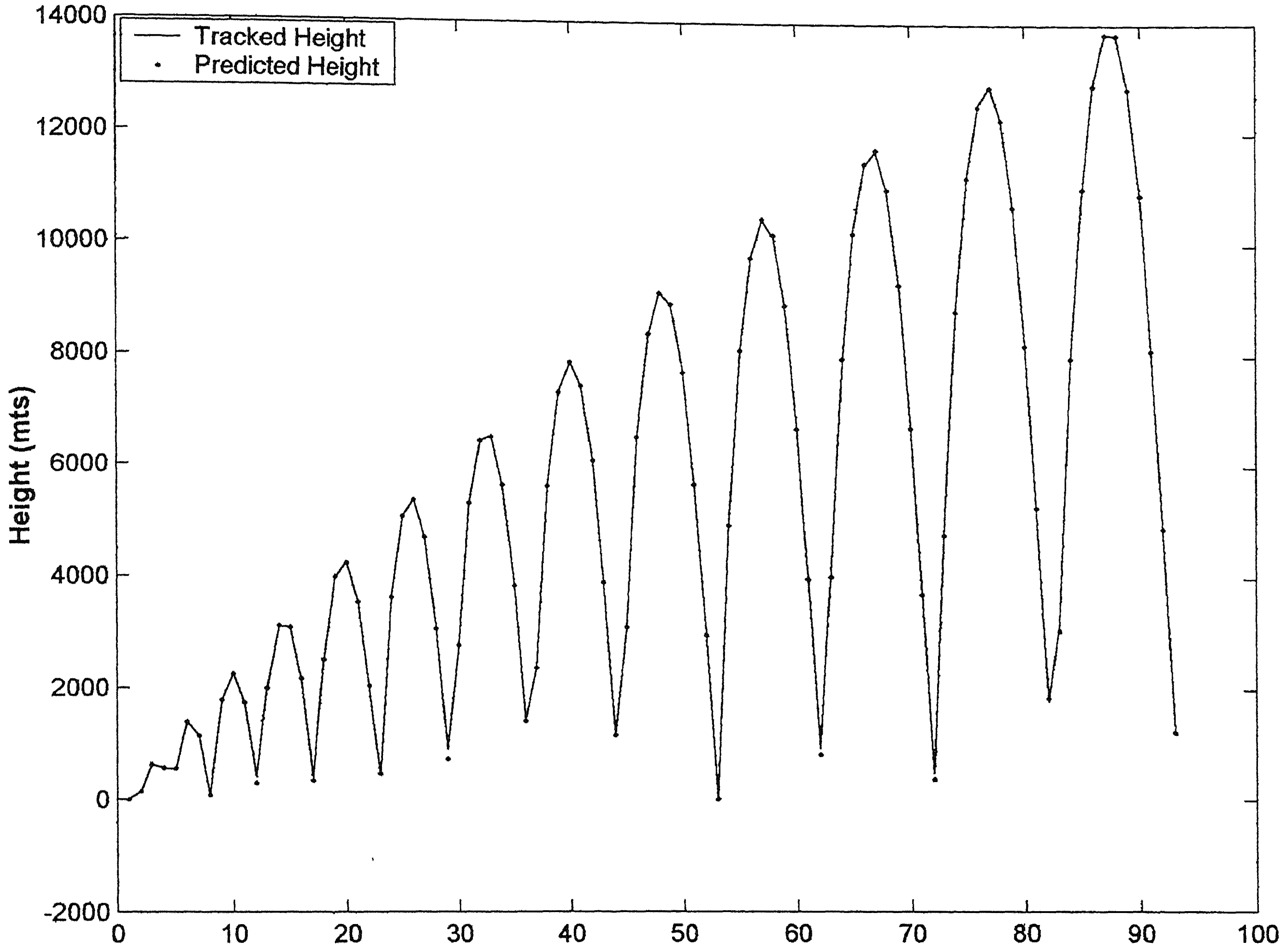


Fig 4.9 Comparison of tracked trajectory and predicted trajectory for various elevations using neural Model 4

CHAPTER 5

CONCLUSION

The validity of neural modeling is demonstrated for four different applications related to modeling the effect of wind for artillery shell. A set of available firing data in form of elevation, wind profile, range etc. are required to train the network with suitable input and output samples: Which of these measured variables would form the inputs and the outputs is decided by the purpose of the neural models.

In particular for four distinct applications, a neural model has been identified and validated for artillery shell. The results of all the models compare well with the measured results. The fourth model has the potential to predict the complete trajectory of the shell under varying/constant wind conditions using radar tracked data. The strength of the neural model lies in the fact that once the network is trained, it can be used for on-line applications on the field of action under prevailing atmospheric conditions.

The conventional approach, i.e., the mathematical models such as in-vacuo trajectory model, modified point mass model, six-degree-of-freedom model require knowledge of all the forces and moments acting on the shell. Evaluation of forces and moments, in turn, require aerodynamic coefficients as inputs and this fact limits the accuracy of predictions because the reliability of available estimates of these coefficients is not always high. In contrast, the proposed neural models do not require any mathematical model or its solution. This implies that the neural models do not require estimates of aerodynamic coefficients. Furthermore, if the neural network is trained on the real data, it will automatically account for the initial conditions and unknown uncertainties in an implicit way. The output of Neural model will help in improving the mean point of impact of a group of shells

Suggestion for future work

1) The training of the neural network depends on the architecture of the FFNNs, the activation function used by the neurons and the values selected for the tuning parameters. From the neural network point of view, lot of scope exists to explore and experiment with new evolving schemes and methodologies for improving the input-output mapping.

2) The present work has used either firing table data provided by ARDE or simulated data (radar tracked or measured). An attempt should be made to seek real firing data including radar tracked and validate the present model for such data. It will be of interest to predict range for known firing angle under varying wind condition using neural models and compare them with the prediction by SDF model. A comparison of results from the mathematical models and neural models would show reliability of the predicted value for real life applications.

3) The present work makes an attempt to evolve neural model using varying wind only. The search must extended to model other varying meteorological conditions like temperature, density etc.

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Appendix A

FEED FORWARD NEURAL NETWORK

The back propagation network consists of one input layer, one output layer and one or more hidden layers There is no theoretical limit on the number of hidden layers but typically there is just one or two Some work has been done [14], which indicates that minimums of four layers (three hidden layers and one output layer) are required to solve problems of any complexities. Each layer is fully connected to the succeeding layer (standard connection).

There are as many neurons in the input layer as there are inputs, and likewise with the output layer. The number of layers and the number of neurons in the hidden layer(s) must be determined by trial and error. There is no quantifiable best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying various architectures to their problems.

Rule 1. As the complexities in the relationship between the input data and the desired output increases, the number of processing elements in the hidden layer should increase.

Rule 2. If the process being modeled is separable into multiple stages, then additional hidden layers may be required. If the process is not separable into stages, then additional layers may simply enable memorization and not a true general solution.

Rule 3 The amount of available training data sets an upper bound for the number of processing elements in the hidden layer. To calculate this upper bound, use the number of input-output pair examples in the training set and divide that number by the total number of input and output processing elements in the network. Then divide the result again by a scaling factor between five and ten. Larger scaling factors are used for noisy data.

Extremely noisy data may require a factor of twenty or even fifty. Very clean input data with an exact relationship to the output might allow the factor to be dropped to around two.

Cross-Validation and Overtraining

One approach to avoid over-training of the network is to estimate the generalization ability during training and stop when it begins to decrease The essence of back-propagation learning is to encode an input-output relation, presented by a set of data, with a multiplayer perceptron well trained in the sense that it learns enough about the past to generalize to the future. The simplest method is to randomly partition the data set into a training set and a test (validation) set From the training set, a validation subset, which are typically 10 to 20 percent of the training set is set aside. The motivation here to validate the model on a data set different from the training set that is used for selecting the architecture of the network The training set is used to modify the weights, the validation set is used to estimate the generalization ability. The architecture of the network is varied till the training set results in MSE less than the prescribed value ε. This architecture is now tested on the test data (which can be one or more) and if the MSE is of the order of 2ε, the architecture is accepted to yield the desired neural model and assumed to be capable of predicting required output for inputs not seen earlier by the network.

Another way of avoiding over-training is to limit the ability of the network to take advantage of spurious correlation in the data. Over fitting is thought to happen when the network has more degrees-of-freedom (the number of weights, roughly) than the number of the training samples when there are not enough examples to constrain the network.

Even though it may give exactly right output at the training points, it may be very inaccurate at other points. An example is a higher order polynomial fitted through a small number of points.

Sufficient Training Set Size For a Valid Generalization

Generalization is influenced by three factors: i) the size and the efficiency of the training set, ii) the architecture of the network, and iii) the physical complexities of the problem at hand. Clearly, we have no control over the last factor, i.e., the physical complexity. We have already discussed the choice of architecture based on training and test data. Once the architecture of the network is fixed, then the size of training set can be derived as follows.

Let M denote the total number of hidden layer computation nodes. Let W and N be the total number of synaptic weights and the number of random examples used to train the network respectively. Let ε denote the fraction of error permitted on test Then, according to Baum and Haussler, [2] the network will almost certainly provide generalization provided the following two conditions are met.

(a) The fraction of error made on the training set is less than $\varepsilon/2$.

(b) The number of examples(N) used in the training is

$$N \geq 32 \frac{W}{\varepsilon} \ln \frac{W}{\varepsilon}$$

where W is the total number of synaptic weights.

Ignoring the logarithmic factor, taking first order approximation, the number of training examples is directly proportional to the number of weights in the network and inversely proportional to the accuracy parameter ε. Then, $N > \frac{W}{\varepsilon}$.